HELSINKI UNIVERSITY OF TECHNOLOGY
Department of Electrical and Communications Engineering

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EEG-based brain-computer interface with visual and haptic feedback

In partial fulfillment of the requirements for the degree of Master of Science, Espoo January 11, 2007.

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Tekijä: Tapio Palomäki
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Tiivistelmäteksti:

Tehokas koehenkilöiden oppiminen palautteen avulla on tärkeää aivokäyttöliittymä tutkimuksessa. Suurimmassa osassa aiemmista tutkimuksista koehenkilöt ovat saaneet palautteen visuaalisena; toiset palautemodaliteetit voisivat paremmin palvella potilaita, joilla on näkövammoja ja käyttäjiä, jotka tarvitsevat näkökykyä muualla. Aiemmissa tutkimuksissa auditiivinen palaute oli merkittävästi huonompi koehenkilöiden opetuksessa kuin visuaalinen palaute. Haptinen (tunto) palaute voisi sopia paremmin aivokäyttöliittymille.

Kuusi liikuntakykyistä, ensikertalaista koehenkilöä saivat haptista tai visuaalista palautetta tai molempia erillisissä sessioissa opetellessaan kaksiluokkaisen aivokäyttöliittymän hallintaa vasemman ja oikean käden kuvittelulla. Kokeita varten toteutettu TKK BCI komponentteineen kykenee reaaliaikaiseen signaalin mittaukseen, signaalien käsittelyyn, palautteen antamiseen ja sovellusten ohjaamiseen. Palautetta annettiin kerran sekunnissa joko näytöllä tai haptisilla elementeillä, jotka kiinnitettiin koehenkilön kaulan alaosaan.

Koehenkilöt saavuttivat keskimäärin 67 % luokittelutuloksia haptisella palautteella ja 68 % visuaalisella palautteella. Yksi koehenkilö saavutti jopa 88.8 % luokittelutuloksen yhdessä sessiossa. Piirrevalinnalla löydetyt vakaat sensorimotoriset rytmit taajuuksien 8-12 Hz ja 18-26 Hz välissä tuottivat parhaimmat tulokset. Haptinen stimulaatio aiheutti vain vähän näkyvää häiriötä taajuusalueella 8-30 Hz.

Tulokset tästä tutkimuksessa näyttävät, ettei haptisen ja visuaalisen palautteen välillä ole selkeää eroa koehenkilöiden oppimisessa. Suurin osa koehenkilöistä kokivat haptisen palautteen luonnolliseksi ja miellyttäväksi. Haptinen palaute voi näistä seikoista johtuen korvata visuaalisen palautteen ja vapauttaa näkökyvyn muihin tehtäviin. Tulosten vahvistamiseksi on tarpeellista tehdä jatkotutkimuksia liikuntakyvyttömillä oikeissa kotiympäristöissä.

Avainsanat: elektroenkefalografia, aivokäyttöliittymä, visuaalinen palaute, haptinen palaute, jatkuva kuvittelu, sensorimotoriset rytmit, taitojen oppiminen

HELSINKI UNIVERSITY OF TECHNOLOGY	ABSTRACT OF THE MASTER'S THESIS

Author: Tapio Palomäki

Title: EEG-based brain-computer interface with visual and haptic feedback

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Abstract:

Efficient training of subjects with feedback is essential to brain-computer interface (BCI) research. In most previous studies, subjects have mostly received visual feedback; other feedback modalities could, however, better serve patients with visual impairment and in tasks, which allocate visual attention. In previous studies auditory feedback was significantly worse than visual feedback during subject training. Haptic feedback (vibrotactile stimulation) could be better suited for brain-computer communication than auditory feedback.

Six able-bodied subjects without previous BCI experience received haptic or visual feedback or both in separate sessions while learning to control a two-class BCI using imagery of left and right hand movements. A BCI system was designed and implemented for the experiments. The TKK BCI consists of components capable of real-time signal acquisition, signal processing, feedback, and control of applications. The feedback was presented once every second either on a screen or with haptic elements attached to the base of the subject's neck.

The subjects achieved average classification accuracies of 67% with haptic and 68% visual feedback. One subject achieved as high as 88.8% accuracy in a single session. Stable features selected from sensorimotor rhythms within the 8-12 Hz and 18-26 Hz frequency bands provided the highest accuracies. Only minor interference using haptic stimulation was observed within the 8-30 Hz frequency band.

The results indicate no clear differences between learning with haptic or visual feedback. Most subjects felt haptic feedback natural and comfortable. Haptic feedback could thus substitute for visual feedback, and render vision available for other concurrent tasks. Further studies especially with motor-disabled patients in real home environments will be necessary to confirm the results.

Keywords: electroencephalography, brain-computer interface, visual feedback, haptic feedback, continuous imagery, sensorimotor rhythms, skill learning

Foreword

This work was done in the Laboratory of Computational Engineering (LCE) at the Helsinki University of Technology (HUT) as part of the EU-funded project, Non Invasive Brain Invasive Brain Interaction with Robots - Mental Augmentation through Determination OF Intended Action (MAIA). LCE was selected as the Academy of Finland's centre of excellence for years 2006-2010. The supervisor of this work was Professor Iiro Jääskeläinen and the instructor M.Sc. Laura Kauhanen.

I would like to thank Professor Iiro Jääskeläinen for the opportunity to participate in this fascinating project. I would like to thank Dr.Tech. Jukka Heikkonen for the advice on scientific work. I would like to thank M.Sc. Pasi Jylänki for giving insight to signal analysis and classification. I would like to thank M.Sc. Janne Lehtonen for the assistance with the operation and development of the BCI system. I would like to express my gratitude to M.Sc. Laura Kauhanen for all the work she has done to make this thesis possible and for the long discussions on research and science. I would like to express my deepest gratitude to my parents for supporting me whenever I needed it.

In Espoo, January 11, 2007

Tapio Palomäki

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Abbreviations and notations

AAR	Adaptive Autoregressive model
ALS	Amyotrophic Lateral Sclerosis
BCI	Brain-Computer Interface
BCI2000	A BCI system framework
CAR	Common Average Reference
COM	Serial Communications Port
CSP	Common Spatial Pattern
CSSP	Common Spatio-Spectral Pattern
C/C++	A Programming Language
ECoG	Electrocorticography
EEG	Electroencephalography
EMG	Electromyography
EOG	Electro-oculography
ERD	Event-Related Desynchronization
ERP	Event-Related Potential
ERS	Event-Related Synchronization
FFT	Fast Fourier Transform
fMRI	Functional Magnetic Resonance Imaging
GUI	Graphical User Interface
HF	Haptic Feedback
HMM	Hidden Markov Model
ISI	Inter-Stimulus-Interval

ITR	Information Transfer Rate
LDA	Linear Discriminant Analysis
LFP	Local Field Potential
LOC	Locus Of Control Of Reinforcement
LMS	Least Mean Squares
MCMC	Markov Chain Monte Carlo
MEG	Magnetoencephalography
MLP	Multi-Layer Perceptron
NIRS	Near-Infrared Spectroscopy
N200	Negative peak 200 ms after stimulus onset
P300	Positive peak 300 ms after stimulus onset
RBF	Radial Basis Function
RJMCMC	Reversible Jump Markov Chain Monte Carlo
RP	Readiness Potential
SCI	Spinal Cord Injury
SCP	Slow Cortical Potential
SD	Standard Deviation
SMR	Sensorimotor Rhythm
SNR	Signal-to-Noise Ratio
SQUID	Superconducting quantum interference device
SSVEP	Steady-State Visual Evoked Potential
Sx	Subject x
TFR	Time-Frequency Representation
TCP/IP	Transmission Control Protocol / Internet Protocol
USB	Universal Serial Bus
VEP	Visual Evoked Potential
VF	Visual Feedback

Chapter 1

Introduction

Patients in paralyzed and locked-in states, usually caused by spinal cord injuries and serious nervous system deceases, have only limited or no communication capabilities. These patients require novel means of communication and interaction for everyday situations; brain-computer interface research attempts to create new technology to improve the life of the patients (Wolpaw et al., 2002). The potential user population which would benefit from brain-computer interface technology has been estimated to be nearly 100 million people (Vaughan, 2006). To reach the people's homes, wide-ranging interdisciplinary research is required to address both psychological and technical aspects. The needs and the preferences of the patients are the key criteria guiding the research (Vaughan, 2006).

Initial research in brain-computer interfaces in 1973 was limited by real-time processing capacity of the contemporary computers; the research in the field is no longer constrained by computing power (Vidal, 1973, 1977). Current brain-computer interface systems are based on both detection of attended external stimulus and self-induced modulation of brain activity; the selection of approach depends on each individual user (Wolpaw et al., 2002; Kubler et al., 2001). Electroencephalography (EEG) is the primary tool for measuring brain activity because it is relatively inexpensive, is easy and fast to set up, and creates no risk for the user. EEG will likely remain popular in future brain-computer interface research. Recent advance in equipment and methods have brought the technology to the point where the systems can be made convenient and small enough for home use.

Attention is shifting to user experience and user preferences (Vaughan, 2006).

Variety, stability, and robustness of available of brain-computer interfaces, however, need to be increased to reach a commercial level of operation. Such systems should be acceptable to the users, easy to use, and fast to set up; the time required during the training of the user and in calibrating the system should also be made as short as possible. The brain-computer interface system should provide the same communication capabilities to individuals with varying conditions such as blindness, deafness, and sensing deficits, and differences in injury location and disease progression. Feedback forms an essential communication channel for brain-computer interfaces. To our knowledge, haptic feedback (vibrotactile stimulation) has received minimal attention in the context of brain-computer interfaces; haptic feedback would offer an additional communication channel for those who are unable to see or hear, or have lost movement capability of their extremities.

This thesis attempts to evaluate whether the efficiency of haptic feedback differs from visual feedback during brain-computer interface training. Provided that haptic feedback and visual feedback are equivalent during user training, haptic feedback would then extend the user population to individuals with blindness; it would also free up visual modality for use in other tasks and help users with difficult visual tasks requiring high precision. The experiments were done with the TKK BCI system that has been implemented as a part of this thesis.

Chapter 1 presents a general introduction to brain-computer interfaces, the brain, and the principles of learning. Chapter 2 gives a detailed description of the methods used in the experiment. Chapter 3 shows the results of the experiment. Chapter 4 discusses the results in the context of previous literature.

1.1 Brain-computer interface systems controlled with brain activity

A brain-computer interface (BCI) is defined as follows: "A BCI is a communication system in which messages or commands that an individual sends to the external world do not pass through the brain's normal output pathways of peripheral nerves and muscles" (Wolpaw et al., 2002). A brain-computer interface system (Figure 1.1) consists of brain signal acquisition by several methods, signal processing by feature extraction and translation of patterns into device commands and feedback (Birbaumer, 2006; Wolpaw et al., 2002; Vidal, 1973). BCI researchers have to take into account what processes generate the observed brain signals, how to measure them and how to turn them into something meaningful.

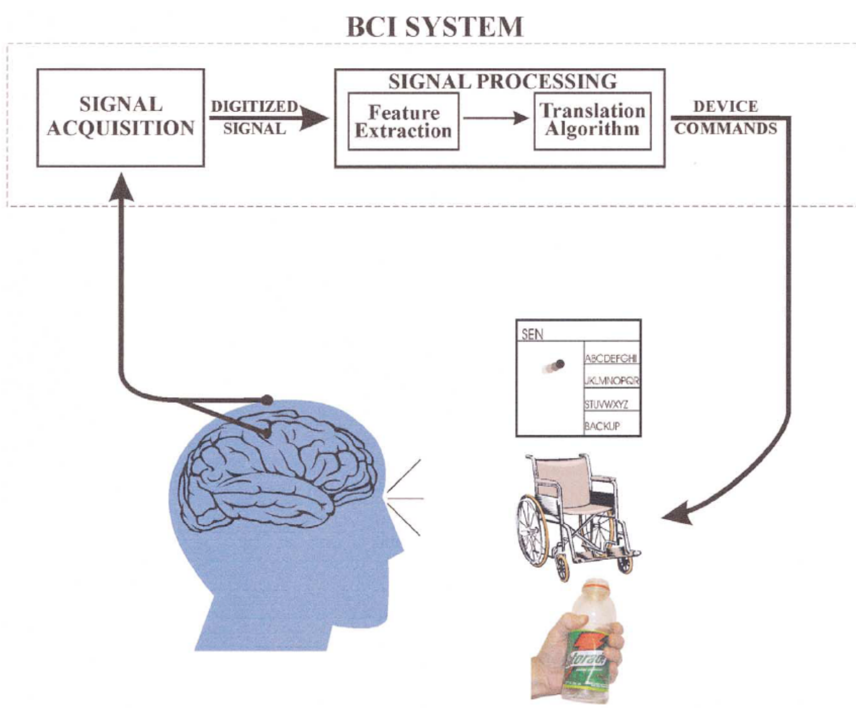

Figure 1.1: Schematic overview of a BCI system: the brain signals are digitized and further processed by feature extraction and translation algorithms. These algorithms produce commands that can control applications. Adapted from Wolpaw et al. (2002).

1.1.1 Brain structure, activity, and plasticity

The cerebral cortex of the human brain is divided into four parts according to their rough physical and functional properties: occipital lobe, temporal lobe, parietal lobe, and frontal lobe (Figure 1.2). The occipital lobe processes visual inputs originating from the lateral geniculate nucleus of the thalamus, which receives direct input from the retina. The temporal lobe has been associated with auditory and category processing. The parietal lobe processes somatosensory stimuli such as touch and pain. The frontal lobe is associated with motor planning and execution, and is also related to memory, personality and other high level functions (Gazzaniga et al., 2002). For BCI researchers, the interest in different areas lies in the type of processing they perform. Different visual responses and motor planning activations can be detected on the respective areas and can serve as the basis for discriminating different brain states for brain-computer communication. The applicability of different brain states depends on the users ability to control these different activations at will (Wolpaw et al., 2002).

Signals from the visual regions in the occipital and parietal lobes, and the motor cortex in the frontal lobe near the central sulcus are most commonly used for BCIs; external stimulus, and real and imaged movements have been reported to activate these areas with great reliability (Wolpaw et al., 2002). The motor cortex (specifically the primary motor cortex) is further divided into several regions according to its functional organization (Figure 1.3); this representation of the human body on the motor cortex is called the human motor homunculus (Gazzaniga et al., 2002). The use of these representations for hands, feet, and mouth regions, among other body parts, are suitable for brain state discrimination (Wolpaw et al., 2002; Kubler et al., 2001).

The information processing of the cortex itself depends on the biological units called neurons, schematically presented in Figure 1.4, which conduct electric signals, called action potentials, across the neuron structures and over to other neurons through synapses. Several different types of neurons exist but they share general properties and structure: the dendrites, the cell body, the axon and the axon terminals. The axon terminals form synaptic connections, usually with chemical transmitters, to the dendrites of other neu-

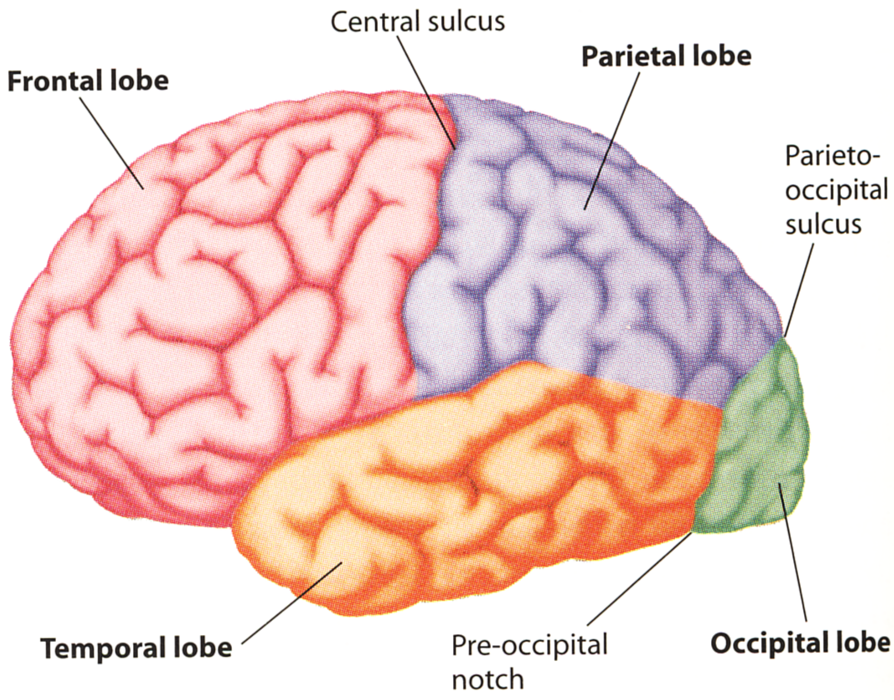

Figure 1.2: The structure of the brain with four lobes: frontal, parietal, temporal, and occipital lobe. The motor cortex, which is important to motor planning and execution, is located anterior to the central sulcus. The occipital lobe provides the signals for visual perception based BCIs. Adapted from Gazzaniga et al. (2002).

rons; the dendrites relay the signals to the cell body. An action potential is generated at axon hillock whenever the potential level in the cell body exceeds a firing threshold. A refractory period of 1 ms in firing limits the amount of action potentials, which propagate through the axon to the synapses; the myelin sheath increases the propagation speed of the signal significantly (Gazzaniga et al., 2002). Brain activity measurements are based on the events that happen in these neurons, in the tissue in the vicinity of the neuron, and in the other biological material and cells close to the neuron population (Gazzaniga et al., 2002; Niedermeyer and Lopes da Silva, 1999).

Plasticity, the ability of the tissue, the cells, the neurons, and the neuron patterns to adapt to changes, constantly changes the underlying structure and affects the stability of the measurements; learning, psychological conditions, injuries, and progressive diseases all contribute to short and long term dynamics in the brain. Learning, the adaptation of neuron populations (by for instance hebbian adaptation in strengths of the synapse) to input data in context of previously learned patterns, can have both short and long term effects;

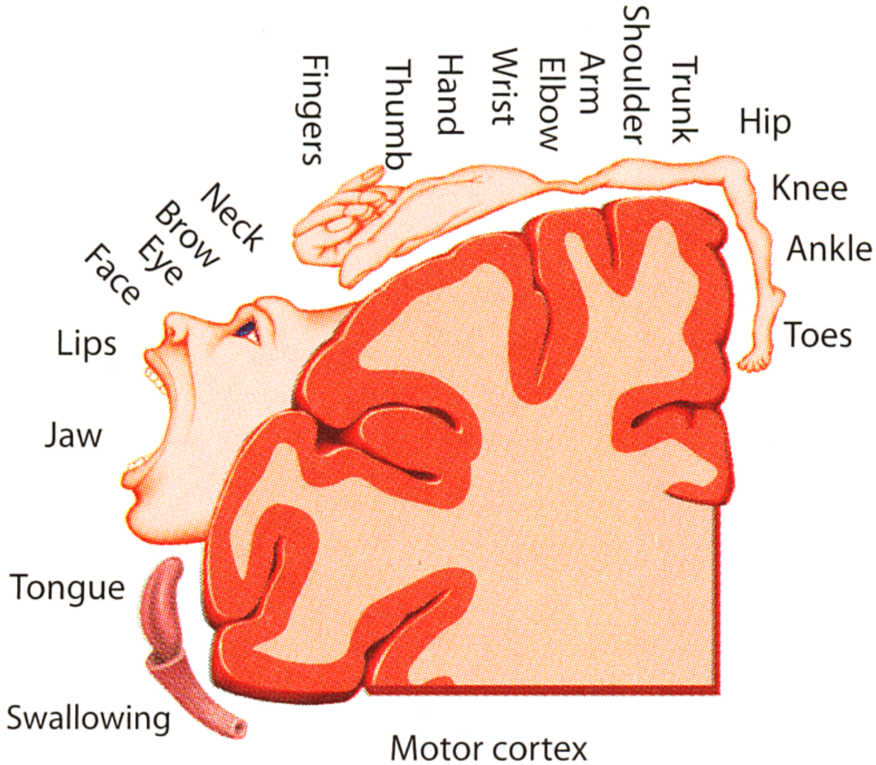

Figure 1.3: The organization of the motor cortex according to human extremities is called the human motor homunculus. A large portion of the surface of the cortex is dedicated to face and hands. Adapted from Gazzaniga et al. (2002).

self-regulation of ones brain activity can be achieved quickly but because of habituation, the skill might require continuously decreasing amount of neurons; the activation detection by computer might become impossible. Injuries, lesions, and neuron deterioration in the brain and the spinal cord may lead to loss of functionality and mobility; nevertheless the brain can bypass damaged regions to some extent in patients with lesion, and retain the representations of affected extremities in patients with paraplegia and tetraplegia; the representation regions might merge to other regions due to inactivity related to the lost functionality. These considerations are particularly important because the BCIs are the most needed by patients with severe injuries and conditions, such as amyotrophic lateral sclerosis (Gazzaniga et al., 2002; Sanes and Donoghue, 2002; Wolpaw et al., 2002).

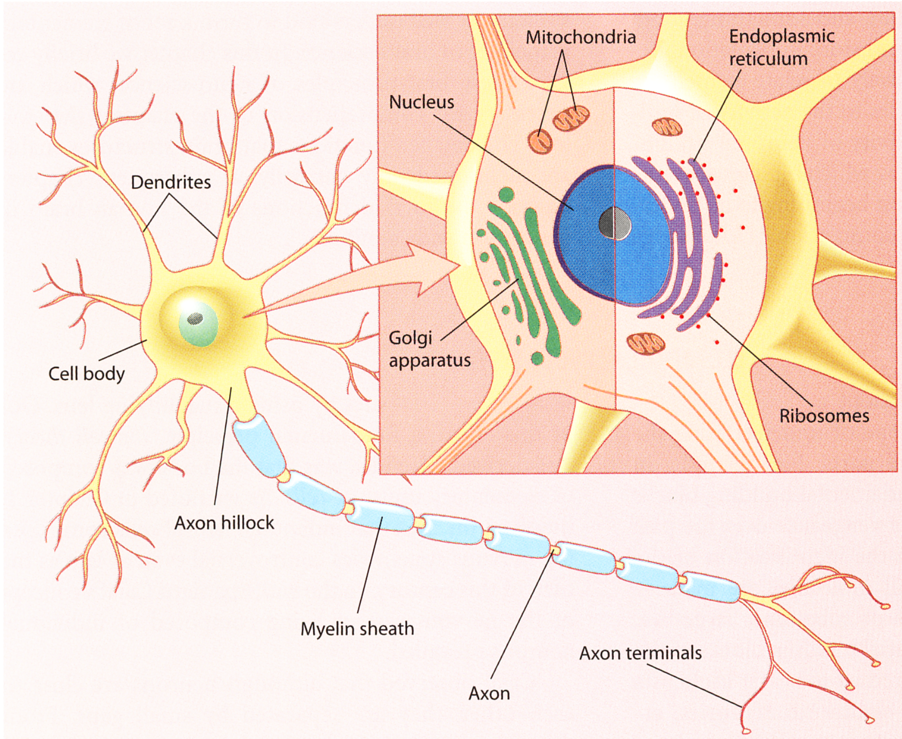

Figure 1.4: The structure of a neuron: Dendrites branch to wide areas and receive signals across synapses. The signals travel to the cell body and continue along the axon if the potential is high enough at the axon hillock to release an action potential. The myelin sheath increases the speed of the signals. Adapted from Gazzaniga et al. (2002).

1.1.2 Measuring brain activity with EEG

Brain activity is the joint activity of single neurons and neuron groups acting at different times (asynchronously) or in synchrony; each neuron in the brain generates changes in electric and magnetic fields, which can be measured. The electric fields are measured as potential differences (voltages) with electroencephalography (EEG), electrocorticography (ECoG), and intracortical grids of electrodes, which provide local field potentials (LFPs). The magnetic fields are measured with magnetoencephalography (MEG). Each active neuron also requires increased amount of oxygen; the local concentration of oxygenated hemoglobin in the blood can also be measured. The changes in hemodynamic response is measured with functional magnetic resonance imaging (fMRI), positron emission tomography (PET), and near-infrared spectroscopy (NIRS) (Wolpaw et al., 2006; Niedermeyer and Lopes da Silva, 1999; Villringer et al., 1993; Cabeza and Nyberg, 2000; Hämäläinen et al., 1993)

The placement of the electrodes is illustrated in Figure 1.5 for electric field measurements: the EEG electrodes are located on the top of the scalp, ECoG electrodes are placed under the dura (a thin membrane under the skull and over the cortex), and the intracortical electrodes are implanted within the cortex. EEG suffers from reduced spatial resolution because of the intervening tissue and the skull; this problem is avoided in both ECoG and intracortical electrode measurements, but with cost of invasive placement of the electrodes involving risks and unknown long term stability. No electrode placement is required for fMRI, PET, and MEG. MEG measures the magnetic fields created by neuronal currents with superconducting quantum interference devices (SQUIDs) (Hämäläinen et al., 1993). PET measures blood flow by recording the radioactive tracer injected into the vascular system of a subject. fMRI measures the concentration of the oxygenated hemoglobin with static and dynamic magnetic fields (Cabeza and Nyberg, 2000). NIRS uses the low-absorption property of near infrared light within the spectrum from 800 nm to 2500 nm (Villringer et al., 1993). Good spatial resolution of fMRI, PET, and NIRS is counteracted by poor temporal resolution (Cabeza and Nyberg, 2000); in addition, MEG and fMRI require a superconductor which makes them bulky and expensive. For these reasons only the methods measuring electric fields will have significant practical value in applications. (Wolpaw et al., 2006). Only EEG is covered in greater detail in the subsequent text.

The standard locations on the scalp for 75 EEG electrodes are shown in Figure 1.6; EEG electrodes with unique names are usually placed according to the international 10-20 or 10-10 systems. The location of each electrode differs from the adjacent electrodes by 10% or 20% of the anion-inion distance (ACNS, 2006). The electrodes are usually attached to a cap and thus if the cap is of the correct size, the electrodes are always in the correct position relative to each other. The correct positioning of the cap requires the measurement of the distance between the back of the head (inion) and the point between the eyes (anion), and the measurement of anion-Cz distance; the latter distance should be as close to half of the former distance, for instance 20 and 40 cm. The electrodes are connected to the scalp with a high-conductivity gel after removing the top layer of the dead skin by scratching it softly.

The EEG signals can be derived either monopolarly with all electrodes referenced to

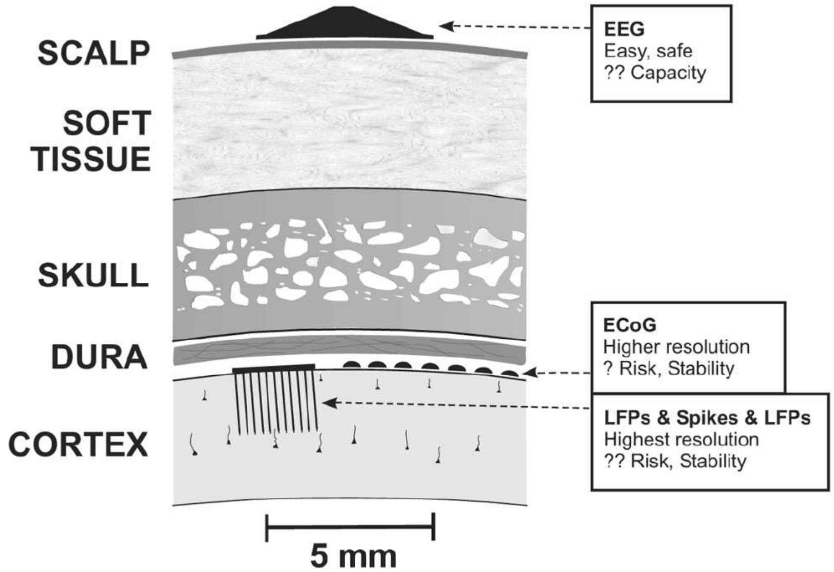

Figure 1.5: Illustration of the layers from cortex to scalp. EEG is measured on top of the scalp and intervening soft tissue and skull alters the signals. ECoG and local field potentials (with potentially better signal quality) are measured under the dura or within the cortex with surgically implanted electrodes. Adapted from Wolpaw et al. (2006).

same location (for instance to ears, to nose, to the location between Fz and Cz, or to Iz), or bipolarly with electrode pairs (Figure 1.7). The derived signals can be further filtered spatially with common average reference filter (CAR), small Laplacian filter, or large Laplacian filter to improve signal quality (Wolpaw et al., 2002).

After the recording and filtering, the signals are available to be printed on paper, to be displayed on a monitor, to control a BCI application or device, or to be saved on mass storage media. Since the first EEG measurements in 1929, several characteristic waveforms have been identified from individuals in different conditions (Figure 1.8); in excited, wake state the EEG signal shows high-frequency activity without clear synchronization. In relaxed, wake state the EEG shows clear synchronization at a specific frequency; this synchronization is thought to originate from an idling neural circuit oscillating at a characteristic frequency. In sleep states, the EEG signals change completely; oscillations at higher frequencies (spindling) are still observed occasionally. In coma the EEG fluctuates as if no activity was present (Gazzaniga et al., 2002). For BCI research, the waveforms present in human beings with normal alertness level (awake) are of most interest. In the following

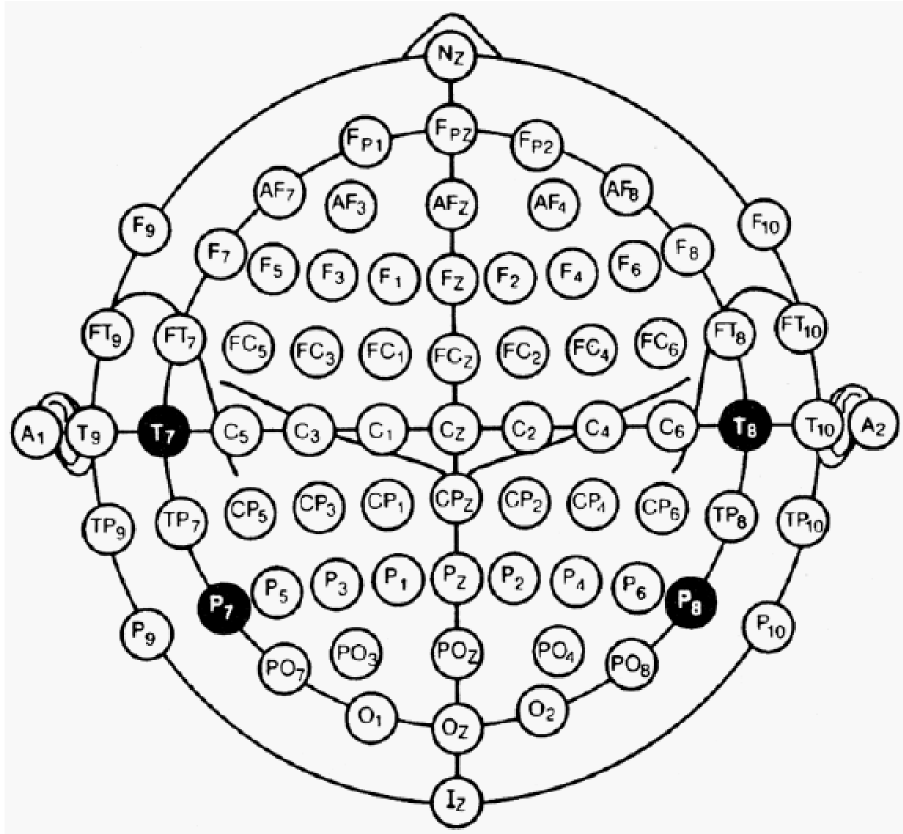

Figure 1.6: The standard electrode locations of the international 10-10 system. The distances between electrodes are 10% of the anion-inion distance measured along the scalp (from the back of the head to the point between the eyes). Adapted from ACNS (2006).

section various characteristic waveforms are covered; some of them can be self-controlled and -induced.

1.1.3 EEG features and feature selection

A feature is a mathematical transformation describing a characteristic phenomenon or waveform in a set of signals (Bishop, 1995). Figure 1.9 illustrates 4 different characteristics that can be found in EEG and cortical measurements: different levels in slow cortical potentials corresponding to expectation (A), evoked potentials in response to a stimulus and selective attention (B), sensorimotor rhythms for motor planning and execution (C), and spiking activity in cortical neurons (D). With appropriate filters the relative strength of the phenomena can be calculated in real-time (Wolpaw et al., 2002).

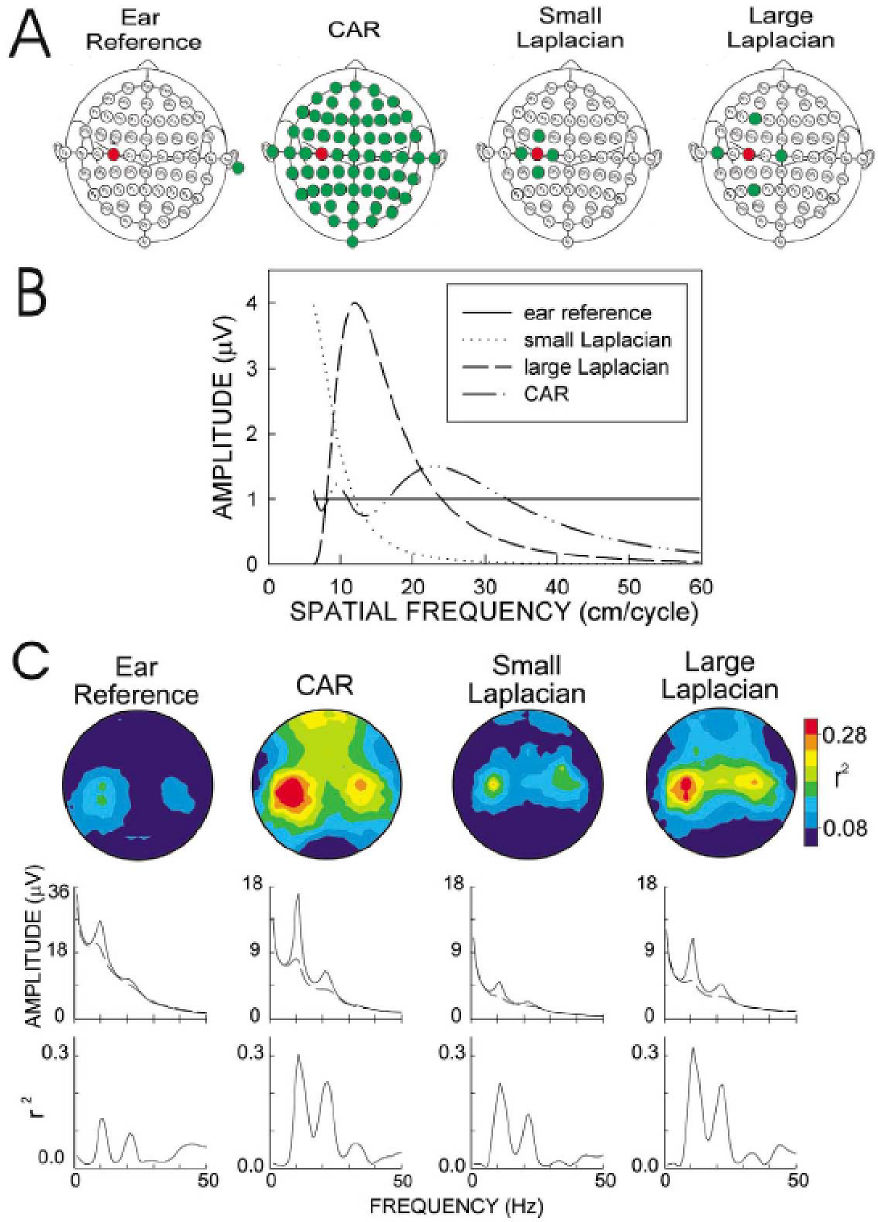

Figure 1.7: (A) A monopolar reference can be either a single electrode placed on the tip of the nose, on either or both of the mastoids, or some other electrode location; other referencing techniques include common average reference (CAR) over all channels, or small or large Laplacian average reference of the nearby electrodes. (B) The selected referencing technique influences the amplitude spectrum of the EEG and can be useful. (C) The correlation of rhythmic activity with electrode locations on the scalp is more clearly visible with CAR and large Laplacian than with an ear reference. Adapted from Wolpaw et al. (2002).

Slow cortical potentials (SCP) appear as slow potential shifts long duration (several seconds), including the readiness potential (RP), which is a shift in potential before the movement onset. Evoked potentials (including visual-, motor-, auditory-, and tactile-evoked

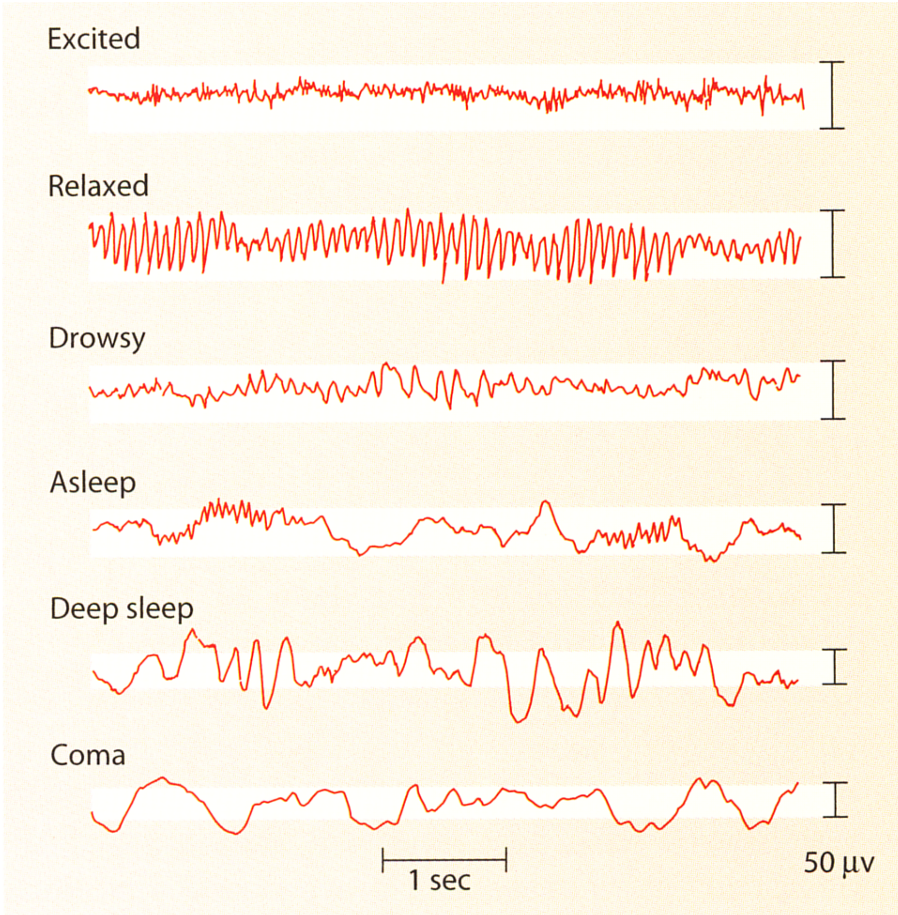

Figure 1.8: The human EEG exhibits high frequency activity with no dominating frequency in excited state. Relaxed state can be seen as dominant alpha band activity (10-12 Hz) at occipital lobe electrodes. Sleep states and coma show only periodical or no fast rhythmic activity. Adapted from Gazzaniga et al. (2002).

potentials) are the native brain response to an external stimulus; the frequently stimulus; the frequently used response is the positive peak in potential level at 300 ms after an infrequent stimulus (the P300 response). Sensorimotor rhythms (SMR), mu-rhythm at 8-12 Hz and beta-rhythm at 18-26 Hz, are associated with motor planning and execution; before the execution of a hand movement, the hand area of the contralateral hemisphere to the movement exhibits event related desynchronization (ERD), the decrease of band power in the mu- or beta- rhythm or both compared to baseline power (Pfurtscheller, 1992; Pfurtscheller et al., 2003). A rebound follows the ERD, exhibiting event-related synchronization (ERS) with strong presence of mu- or beta- rhythm or both. Cortical neuronal activity from single cells is seen as spiking in the recorded signal (Wolpaw et al., 2002).

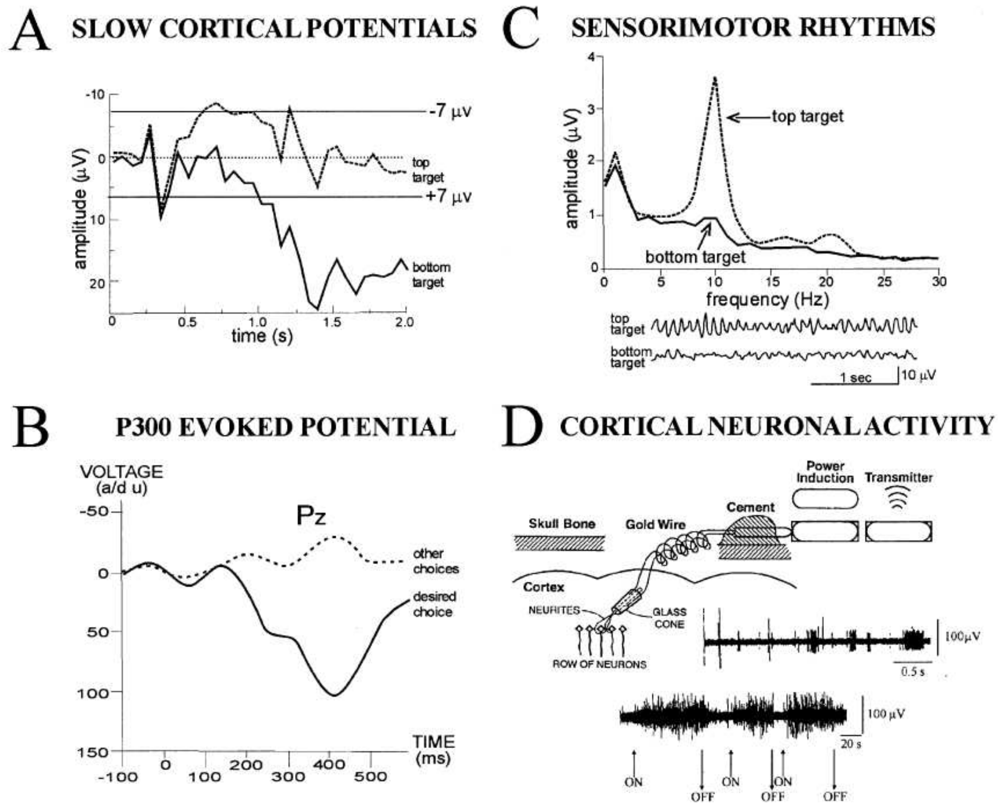

Figure 1.9: Commonly used features of the EEG signals: (A) the slow cortical potentials, such as readiness potentials, (B) averaged P300 potentials in response to visual stimulus and attention, (C) sensorimotor rhythms related to motor planning and execution, (D) spiking of invasively recorded LFPs. Adapted from Wolpaw et al. (2002).

The general idea of features is to separate as well as possible different brain states from each other. The feature selection process aims to discover a set of features, which would best discriminate a number of brain states with a classifier; depending on the selected classifier, however, the results may differ greatly (McFarland et al., 2006; Bishop, 1995).

1.1.4 Feature classification

The discrimination of brain states is challenging because the measured signals are often noisy; a statistical classifier with a noise model is required. The purpose of the classifier is to divide the input feature space into regions, classes (Figure 1.10), which correspond to each different task the subject was asked to perform. With this knowledge, the classifier calculates the probability of all the classes for signals at a time point; the classifier selects the class with highest probability with associated confidence limits. However, a classifier needs to be initialized and trained with sufficient amount of signal data before it can accomplish the classification task with high accuracy. (Bishop, 1995; Wolpaw et al., 2002).

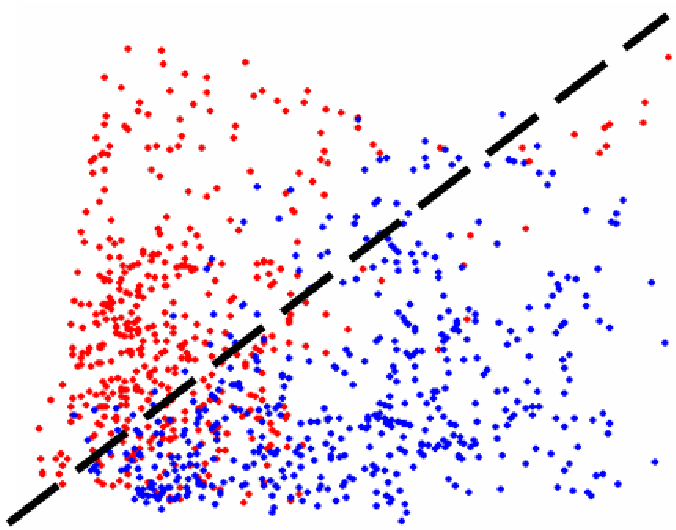

Figure 1.10: An example of a feature space with two classes. In the example, red dots indicate samples of Class 1 and blue dots samples of Class 2. The black line represents the decision border of the two classes for a linear classifier.

The classifier can be for instance a linear model, a non-linear neural network such as multi-layer perceptron (MLP) network, or a radial basis function (RBF) network (Bishop, 1995). A common approach is to build a static classifier with methods such as common spatial patterns (CSP) (Müller-Gerking et al., 1999; Townsend et al., 2006) and common spatio-spectral patterns (CSSP) (Lemm et al., 2005). Gradual changes in recording environment (outside interference), in the signals (changes in impedances), and in the brain (learning) may reduce the effectiveness of the classifiers; these changes require adaptive versions of the classifiers, which can improve accuracies up to 8% compared to the static counterparts (Sykacek et al., 2004). Bayesian approaches are able to cope with the mentioned non-stationarities, and also with uncertainties in signal, and classification results (Sykacek et al., 2004; Roberts and Penny, 2000). Improvements to classification results are expected when the dynamics of the EEG signals over time are taken into account. Hidden Markov models (HMM) treat the signals as statistical process and thus incorporate the time information of the data; HMMs are currently the most used approach in voice recognition (Obermaier et al., 2001; Penny and Roberts, 1999). Causal relations in neural systems, the Granger causality and dynamic causal modeling, could also serve in classification of brain states for online (real-time) BCI; the complexity of the methods, however, might not meet the real-time processing requirements (Kaminski et al., 2001; David et al., 2006). The previously mentioned classifiers can be extended to handle more classes than two.

Each classifier is able to produce information (selections) at varying rates. The information transfer rate (ITR) describes a theoretical measure of communication capacity of an information channel, measured in bits per trial or minute (Wolpaw et al., 2002). An efficient classifier with a high information transfer rate outperforms classifiers with low ITR. The ITR of a classifier depends on the number of classes (brain states), the classification accuracy, and the classification interval; the ITR of a classifier with two classes at 100% discrimination accuracy is equivalent to a classifier with four classes at 80% accuracy. More details on the measurement of information transfer can be found in Schreiber (2000).

1.1.5 Application and device control with BCI

BCI training experiments typically include initial adaptation of a classifier, user training with the classifier, and testing the achieved control. Initial adaptation of the classifier usually occurs after several cued (supervised) recording sessions, possibly without feedback (Wolpaw et al., 2002). Immediate feedback on performance is provided to the user in the subsequent cued (supervised) training sessions; the feedback can be either discrete or continuous and presented in visual, auditory, or tactile form. The classifier can be trained real-time (online) with or without cues; this adaptation is continuous adjustment of the classifier both to spontaneous changes in signal features and to the user's adaptation to the BCI system. This level of adaptation is uncommon to current BCIs (Wolpaw et al., 2002). In the uncued (unsupervised) testing sessions the user evaluates the usefulness of the BCI; with sufficient control the user can continue to use the BCI in the desired environment. Periodically cued (supervised) retraining of the classifier, however, might be required (Wolpaw et al., 2002). Fully adaptive BCIs would require no or very little training after initial calibration.

Applications and devices require inputs in various forms: one program requires binary yes and no commands, and another device requires joystick-like control in several dimensions. The required inputs are generated from the output of the classifier; a classifier with a higher information transfer rate provides faster and more extensive control of the inputs (McFarland et al., 2006). The operation mode of the BCI can be either synchronous (system-paced) or asynchronous (self-paced): in synchronous mode the BCI is available periodically, and in asynchronous mode the BCI is available continuously. With an asynchronous BCI the user can issue commands at will; this behavior is close to the natural way of controlling devices and applications. An asynchronous BCI is, however, difficult to implement reliably; most of the present BCIs are still synchronous (Mason et al., 2006).

Standard interfaces should be used to ensure the compatibility of the BCI with other applications, and benefit from interchangeability of the parts (modules) of the BCI. These interfaces would enable quick access to modules containing functionality required to use different source signals, features extraction algorithms, classifiers, and applications (Cincotti et al., 2006). An attempt to create such a BCI system is the BCI2000 software framework, currently freely available to research groups (Schalk et al., 2004).

1.2 Previous BCI system implementations

The following section reviews an interesting set of online BCI systems. Most of the reviewed systems are controlled with EEG. This focus was selected because building an EEG-based BCI is relatively inexpensive; EEG also offers high temporal resolution and mobile measurement devices in contrast to other methods.

1.2.1 The first BCI, with visual evoked potentials

The term brain-computer interface was first coined in 1973 in the early work of Jacques Vidal (Vidal, 1973), who built the first EEG BCI system presenting immediate feedback to the subjects. Faster equipment helped to renew the system in 1977 (Vidal, 1977) to use visual evoked potentials (VEP). The locations of the electrodes were on the occipital lobe, at O1, O2, Pz and Iz, and referenced to Oz; the Oz location was measured against an ear reference. The frontal lobe electrode Fz was recorded for ocular artifact detection. The bandwidth of the recording was 1-70 Hz. The duration of each data epoch was 400 ms starting 50 ms before stimulus onset. The stimulus target was a red, diamond shaped checkerboard which flashed for 30μs in either left, right, up, or down side of the central fixation point (Figure 1.11).

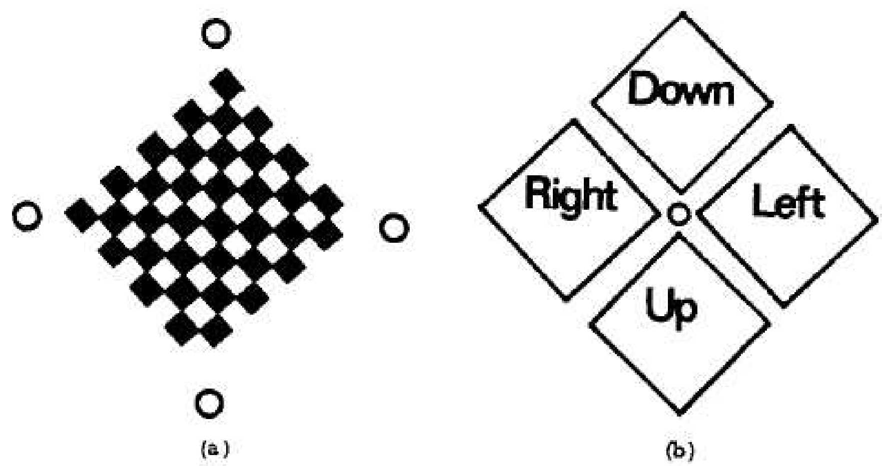

Figure 1.11: (a) The checkerboard stimulus and the four fixation points, and (b) the corresponding selection directions. Adapted from Vidal (1977).

The stimuli activated different locations of the occipital lobe depending on direction of the movement selected by the subject. The subject's task was to escape from a maze. The rate of correct single epoch detection was over 90% on average: for evoked potential systems this was considered to be the lower limit, not the upper limit. Unfortunately no information transfer rates were calculated and provided in the original treatment; however, because of the single epoch classification, the subject could make 2.5 choices per second. In this paper the available computer power was considered to suffice for future approaches requiring high complexity calculations.

1.2.2 P300 response for BCI spelling

This BCI spelling program (Farwell and Donchin, 1988) was the first system to utilize the P300. The stimulus was presented visually as symbols in a 6 x 6 grid (Figure 1.12); every row and column flashed for 100 ms once in every trial, totaling 12 flashes with varying inter-stimulus-interval (ISI) of 500 ms and 125 ms. The subject's task was to attend to a symbol and count the flashes; the attended symbol therefore flashed twice, creating a rare and task-relevant, the "oddball", response.

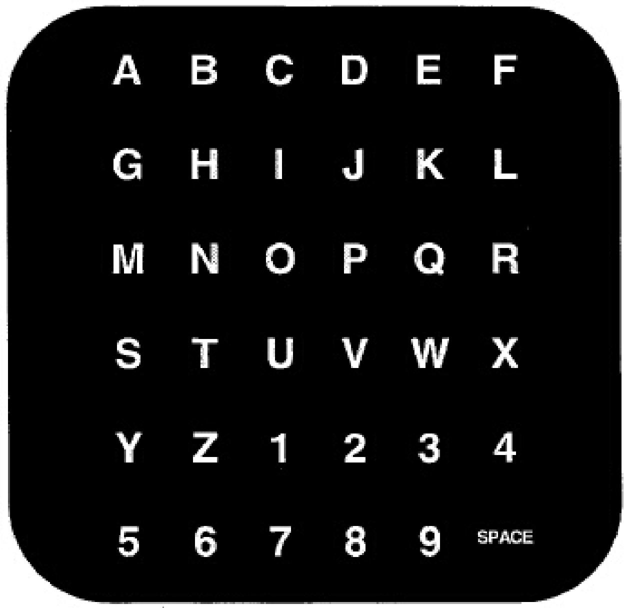

Figure 1.12: The 6 x 6 grid of stimulus with flashing rows and columns of numbers and letters. Adapted from Farwell and Donchin (1988).

The responses were measured at Pz, referenced to linked ear potentials; the used bandwidth was 0.02-35 Hz and the sampling rate was 50 Hz. Four subjects participated in two sessions, the first of which was a familiarization session. The subjects were asked to type the word 'BRAIN' into a spelling program and press the 'talk' button to synthesize the word through speakers. All four subjects were able to select correct letters and activate the synthesizer. Different criteria were compared for best subject performance; with the best criteria (stepwise linear discrimination analysis and peak selection), the required response averaging time for reaching 80% and 95% accuracies were on average 20.9 s and 26.0 s, respectively. The corresponding information transfer rate at 95% accuracy was

12.0 bits/min.

1.2.3 Thought translation device with slow cortical potentials

The thought translation device (Birbaumer et al., 2000) uses slow cortical potentials (SCP) in a language support program to select symbols, pictures and letters. The slow cortical potential reflects the excitation level of the brain networks; the subjects can learn to control the SCP with well-known learning rules. The SCP was measured with an 8-channel EEG device with long time constant (3-16 s) and sampling rate of 256 Hz; the EEG was recorded at electrode locations C3, C4, Pz, Fz, and Cz. During the training phase the subject received visual feedback by a ball-like light moving up and down according to the SCP level; a happy face was presented to the subject for successfully achieving desired potential changes. After reaching a stable accuracy of 75% the subjects began practicing with the language support program. In the language support program the subject indicated a selection by generating a SCP shift; the group of letters were split in half until only one letter remained and was selected; the next selection process followed. An erase function was provided when the subject rejected two subsequent groups. In the study, three patients with varying injuries and loss of movement capabilities were able to achieve reliable control; accuracies ranging from 80 to 95% were possible, enabling free spelling for the patients (Figure 1.13). Two of the patients continued to use the system after the experiment and have been able to maintain their level in the new skill.

1.2.4 Hand orthosis controlled by a tetraplegic

The goal of the project, based on the Graz BCI developed in the University of Graz in Austria, was to build an electronic hand orthosis (Figure 1.14) to aid the grasping of the left hand of a tetraplegic patient, and to give feedback of the controlled EEG mu and beta oscillations (Pfurtscheller et al., 2000). The bipolar electrode pairs were placed 2.5cm anterior and 2.5cm posterior to C3, C4, and Cz; the signals were recorded with bandwidth of 0.5-30 Hz at a sampling rate of 128 Hz. Each session, lasting for 60min, was divided

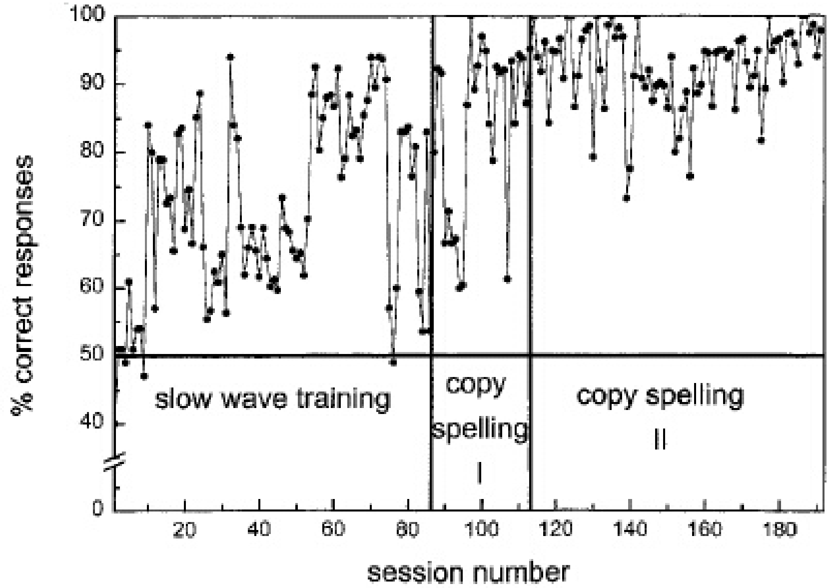

Figure 1.13: The accuracies for patient 003 in sessions of slow wave training, and copy spelling programs I and II. Adapted from Birbaumer et al. (2000).

into 8 s trials with 2 s of baseline in the beginning of a trial. After the baseline period there was a warning stimulus, and after 1 s a visual cue, an arrow pointing to left or right, lasting for 1.25 s. The task was to imagine left vs. right hand movements and right hand vs. both feet movement during the remaining 4 s period. The adaptive autoregressive model parameters (AAR) of the EEG signals were used as the features; the features were classified using linear discriminant analysis (LDA). The classification performance was 65% on average during the first 28 sessions with left vs. right hand imagination; during the sessions 29-53 the accuracy improved to 75% by trying various imagination strategies. In the following sessions the strategy was changed to imagining both feet vs. right hand, and as the result the accuracy improved to about 95%; the information transfer rate, however, remained low because of a long trial length of 8 s. The tetraplegic patient was effectively controlling the 15-18 Hz oscillations (Figure 1.14); with some remaining movement in left biceps the patient was able to eat his first apple with the help of the hand orthosis.

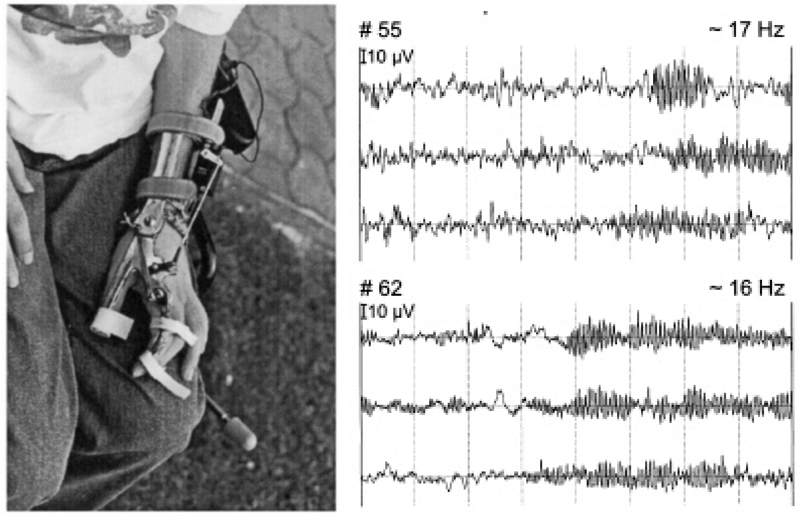

Figure 1.14: Left: the hand orthosis in the patients left hand. Right: the 16-17 Hz activity of the subjects EEG during feet imagery and right hand imagery in two sessions. Adapted from Pfurtscheller et al. (2000).

1.2.5 Video game control with asynchronous BCI

The low frequency asynchronous switch design (Mason et al., 2004) was an effort on a self-paced BCI, attempting to move towards more natural device control. The subjects' first task was to practice the control of the BCI and the second task was to test the achieved control by playing a video game designed for the BCI. The signals were recorded from six bipolar electrode pairs on the scalp: F1-FC1, Fz-FCz, F2-FC2, FC1-C1, FCz-Cz, and FC2-C2, with bandwidth of 0.1-30 Hz at sampling rate of 128 Hz. Two additional electrodes measured the electrooculographic activity near the right eye. A custom feature extraction algorithm was used for the bipolar EEG data to create a custom, six-dimensional feature set. Once the features satisfied an activation criterion, the switch was turned on with value 1; otherwise the value was 0. The practice sessions were conducted in a supervised, synchronized environment; the warning stimulus was presented for 1 s after which the task stimulus was presented for 0.5 s. The feedback was given 3 s after the task stimulus and was presented for 1 s. The asynchronous switch was activated by imagined index finger flexion; the subject could report false activations during a 4-second report period with a pneumatic sip and puff switch. In the test session, the subjects controlled an avatar in a video game by turning it left with the BCI; the avatar would bounce off the walls and the obstacles in the environment (Figure 1.15).

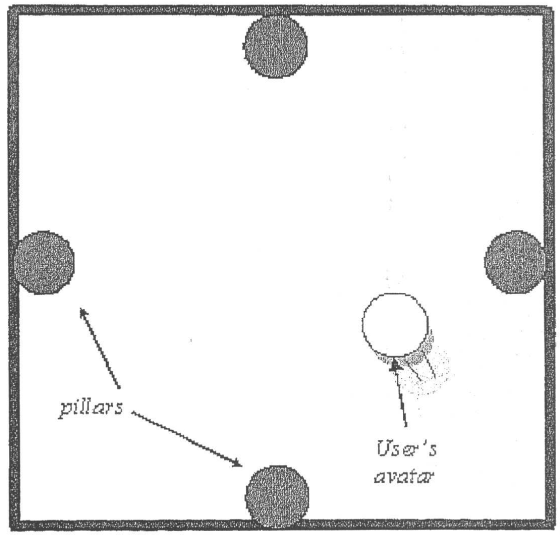

Figure 1.15: The Avatar moving in the environment, bouncing off the walls and the obstacles. Adapted from Mason et al. (2004).

The experiment consisted of six 1-hour sessions, of which the first was a customization session, the two following were practice sessions and three last ones were test sessions. The subjects, four able bodies, and four patients with high-level spinal cord injuries and no motor function in their hands, were able to achieve overall classification rates greater than 94%, with false positives less than 4%.

1.2.6 Noninvasive two-dimensional cursor control

Multidimensional BCI control had been thought to be attainable only with invasive strategies; two-dimensional control in previous EEG-based BCIs was weak. The Wadsworth BCI (Wolpaw and McFarland, 2004), built on top of the BCI2000 framework (Schalk et al., 2004), was designed to achieve reliable 2D control with EEG. The subjects were trained to control two different frequency bands in two separate areas of the brain; subjects controlled the mu and beta bands in the sensorimotor areas near electrodes C3 and C4 with various motor imagery strategies. The EEG was recorded at 64 standard locations with an ear reference; the bandwidth of the recordings was 0.1-60 Hz and the sampling rate was 160 Hz. The coefficients for a linear translation algorithm were optimized with the least mean squares (LMS) algorithm. A target was presented in eight locations on the borders of the screen, with two target locations on each border (Figure 1.16). In this standard center-out experiment, the subject attempted to move the cursor, appearing at the center of the screen, to the target within 10 s; the target flashed to indicate reward for successful control.

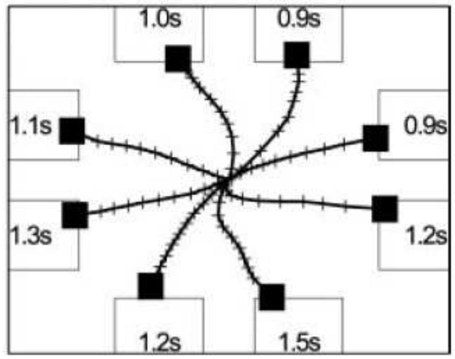

Figure 1.16: The standard center-out task where the cursor would appear in the center of the screen. The time to reach one of the eight targets for one subject is displayed in the corresponding target box. Adapted from Wolpaw and McFarland (2004).

During the experiment the control was horizontal, vertical or combined 2D control, depending on the subject's progress. The subjects participated in daily sessions of a total of eight 3-min runs, with 1-min breaks; the number of sessions varied from 22 to 68 for the four subjects. The subjects reached 89%, 70%, 78%, and 92% accuracies of acquiring targets with the cursor within the time limit. The two seriously injured subjects achieved the highest accuracies; one paraplegic patient could independently control the 12 Hz activity at C4 and 24 Hz activity at C3 (Figure 1.17). Vertical and horizontal control was highly correlated with corresponding target direction; the correlation with the opposite direction was minimal, indicating that the directions of 2D control were independent.

1.2.7 A BCI based on steady-state visual evoked potentials

A BCI (Wang et al., 2006) was based on the steady-state visual evoked potentials (SSVEP), which are generated in response to visual stimuli flashing at different frequencies and are detectable in the visual cortex. The subject was instructed to attend to the selected stim-

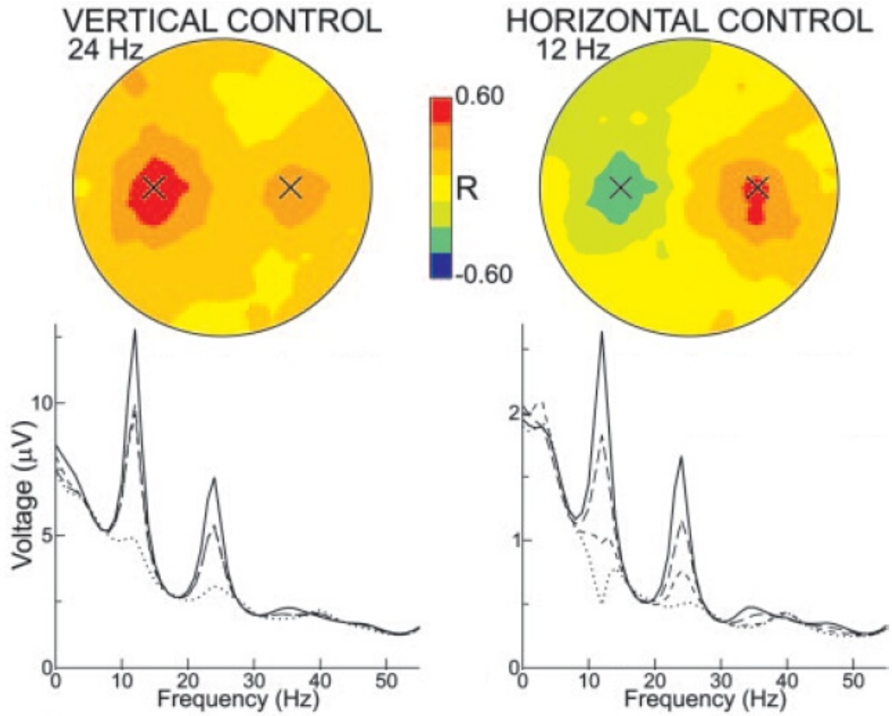

Figure 1.17: The correlation values and spectral component levels for the paraplegic patient for vertical and horizontal control. Adapted from Wolpaw and McFarland (2004).

ulus; the response was then detected as the highest peak in the EEG amplitude spectrum at the stimulus frequency of the attended target in the center of the visual field. The EEG was measured in 13 locations between Pz and Oz (using ear reference); bandwidth was 4-35 Hz and the sampling rate was 256 Hz. The different stimuli were presented with integer frequencies between 9-17 Hz; specific frequencies for each subject were selected to avoid confusion with dominant rhythms like mu at 8-12 Hz. The controlled keyboard had 13 buttons; because of the stimulus frequency intervals of 0.25 Hz and lowest frequency of 13 Hz, none of the used frequencies resided in the mu band. The responses to the stimuli were calculated with a 1024-point fast fourier transform (FFT) of the EEG (Figure 1.18). The 16 subjects in the laboratory and the 10 subjects in a rehabilitation center with various motion disabilities were able to achieve average information transfer rates of 43 bits/min and 21 bits/min, respectively. The results indicated the BCI would be applicable to over 90% of the people, and with high ITR. It should be noted that the usable stimulus frequency range is different for each subject and the range is not necessarily continuous (Figure 1.18).

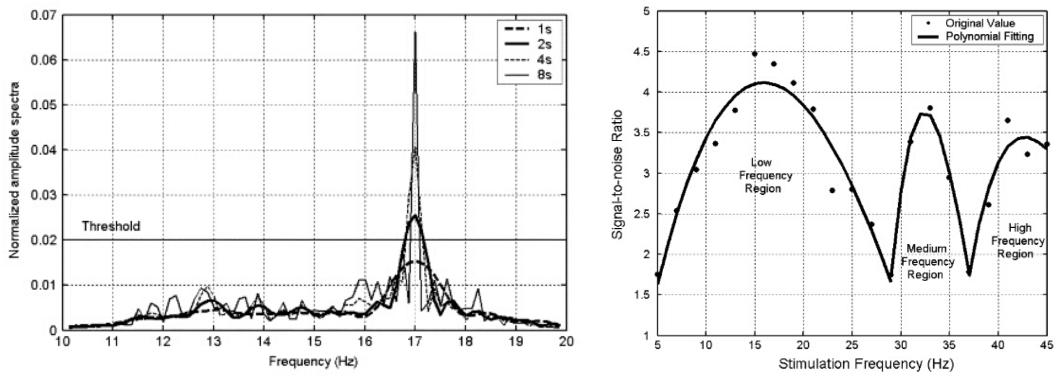

Figure 1.18: Left: Fast Fourier Transform (FFT) of the EEG when the subject was attending a 17 Hz stimulus; the corresponding peak is clearly visible and over a threshold value. Right: Signal-to-noise ratio (SNR) of the stimulus in range of 5 to 45 Hz; it has peaks at 15, 32, and 42 Hz, and minimum values at 5, 30, and 37 Hz. Adapted from Wang et al. (2006).

1.2.8 Invasive BCI control by a tetraplegic

In this rare occasion of invasive human brain-computer interface experiments, a 10 x 10 electrode grid of the size of 4 x 4 mm (Figure 1.19) was implanted into the primary motor cortex (M1) hand area called the 'knob' in the left hemisphere of the patient's brain (Hochberg et al., 2006); the patient's complete tetraplegia, caused by spinal cord injury (SCI) to C4 (ASIA A), prevented movement below the neck. The recordings were gathered in 57 consecutive sessions during 9 months. The spiking in the MI area was found to be still present three years after SCI.

The patient's task was to imagine series of movements; the observed patterns were similar to patterns seen in monkeys. A linear filter algorithm with manually placed time-amplitude windows was used during a technician-guided cursor following task; because of the linear filter, however, the fixation of the cursor to a single location was difficult. The subject acquired 73-95% of the targets in the center out task, with mean time of 2.51 s per target; as a comparison, able-bodied performed the same task using a computer mouse in a mean time of 1.06 s per target. The patient also practiced to operate other devices: an e-mail program, a paint program, a hardware control interface for volume control etc., a video game 'Neural Pong', and two robotic devices (a prosthetic hand for object grasping, and a multi-jointed robotic limb for object transportation). The learning of these tasks was

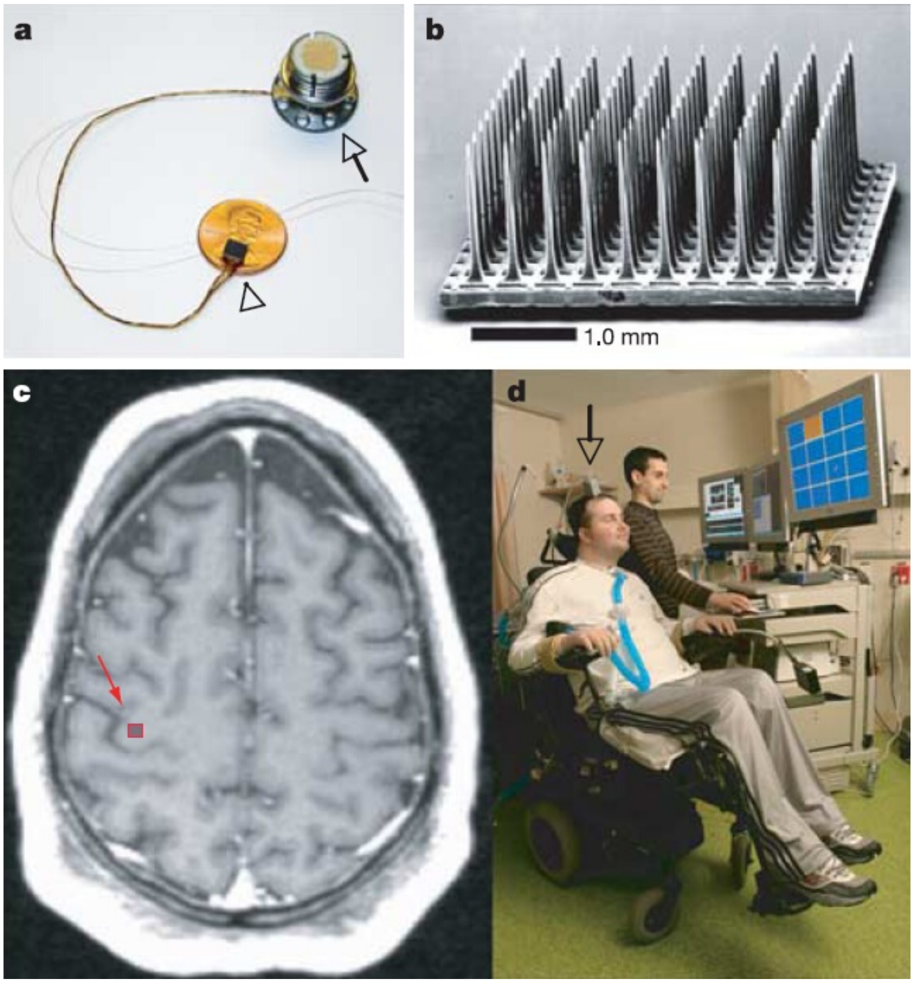

Figure 1.19: (a) The implanted electrode array placed on top of a coin. (b) The 10 x 10 array of microelectrodes. (c) The implantation area in left hemisphere. (d) The patient participating in the experiment. Adapted from Hochberg et al. (2006).

fast and they were performed while the patient was talking.

1.2.9 Readiness potential and mu-rhythm event related desynchronization

The Berlin BCI (Blankertz et al., 2006) requires minimal subject training, relying on machine learning techniques; both the readiness potential as well as the event related desynchronization in the 7-14 Hz band serve as the control features (Figure 1.20). The rapid control of the readiness potential and the event related desynchronization was achieved in initial sessions by imagining left hand, right hand and feet movements without feedback for several sessions. A binary classifier was trained once the discrimination accuracy of two of the imagery types reached 75-95%. EEG was measured with 118 electrodes along with electro-oculography (EOG) and electromyography (EMG). The subjects learned to use three different feedback applications: a horizontal cursor, a rate controlled horizontal cursor, and a baskets game with a horizontally controlled dropping ball. The subjects achieved average accuracies of 80-95% and average information transfer rates of 7-25 bits/min, depending on the feedback application.

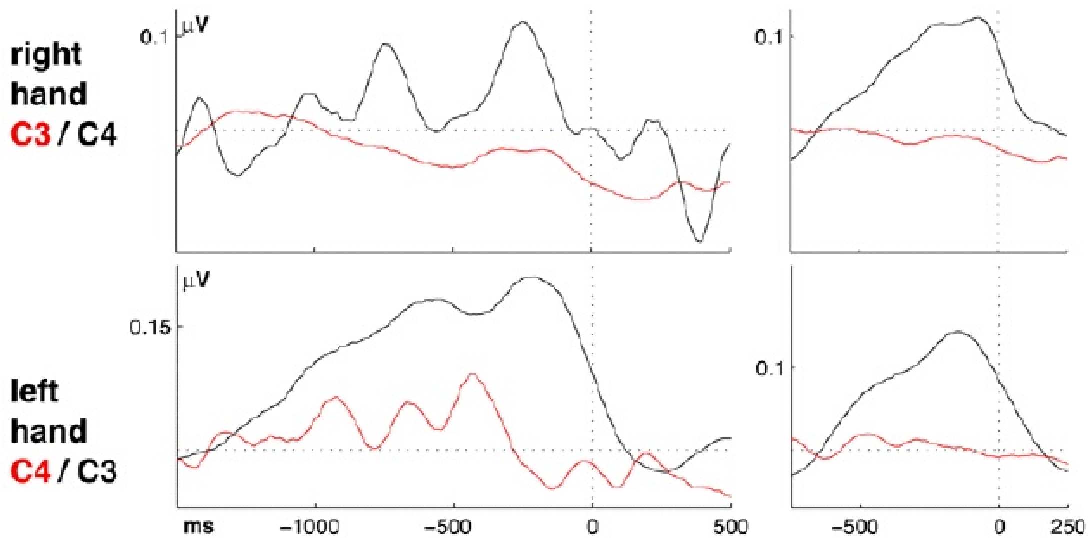

Figure 1.20: The mu-rhythm event related desynchronization (decreased band power) in the hemisphere contralateral to the side of real finger tapping; the tapping intervals are 2 s (left) and 1 s (right). Adapted from Blankertz et al. (2006).

1.3 Learning to use a BCI

The subsequent section reviews the principles of human learning and instruction, learning BCI with feedback, imagery techniques for brain activity modulation, and considerations of parallel machine and human learning. These topics cover the human behavioral aspects of BCI operation and are important for all BCI research.

1.3.1 Principles of human learning and instruction

No general view or unified theory of learning processes or of instructional methods exists; the views, theories, and studies in the field are based on a variety of non-pervasive assumptions. The studies are affected by numerous application fields with their own approaches and interpretations (Glaser and Bassok, 1989).

The study of instruction concentrates mainly on three categories: competence (knowledge and skill) of the students, initial competence and ability of the students, and learning process to acquire desired competence. The study of competence, including memory and language, has received most attention; the least studied area is human learning, which is most related to BCI research. New skills acquired during the learning process have been suggested to develop from a propositional approximation to a well-tuned functional structure; according to the knowledge compilation theory ACT, the acquired skills and knowledge gradually become chunked (compiled and optimized), unconsciously performed, and automatically applied. Skill acquisition occurs during problem solving; the problem should be presented in ideal problem-solving structure guiding in the right direction; immediate error correction, and the model provided by an expert ensure maximal correct performance. For efficiency, the memory workload caused by the environment should be minimal during skill acquisition. Self-regulation (monitoring) of skills, frequently used by experts in different fields and professions, enhances the knowledge of the applicability of the skills; skill monitoring strategies include questioning, clarifying, summarizing, and predicting; at final stage the student may be able to self-direct the learning process. The learning process can also be supported by cooperative and interactive learning with other students and the expert. (Glaser and Bassok, 1989).

Learning to self-regulate imagined motor movements is a common control strategy for BCIs; thus motor skill learning is important. Recent increase in the number of studies in motor skill learning processes has prompted some confusion regarding the participating neural structures and mechanisms; there exists a need for complete theories supported by experimental data. A recent motor skill learning theory proposes that motor control processes are the basis of skill learning. The control-based theory consists of 3 principles: the neural separability principle (anatomically distinct parts for separate motor components), the disparate representation principle (cognitive components have differing representations), and the dual mode principle (conscious or automatic execution). These principles form a parallel network architecture with two mechanisms of skill learning: learning through individual process tuning and learning through the strategic process. The individual process tuning may alter perceptual-motor integration, sequencing, and other dynamic processes; only when movement is executed out of awareness and feedback on movement accuracy is available, the learning may occur in small changes. The strategic process may select high-level goals, such as goal for movement, while conscious. (Willingham, 1998).

In spite of recent increasing efforts, the integrative models of motor skill learning have just begun to emerge, combining the neural mechanisms with previously presented learning theories (Hikosaka et al., 2002).

1.3.2 Learning with feedback

Feedback provides instant or delayed information on the success of solving a problem or carrying out a task; in BCI context, feedback on brain-activity assists in learning self-regulation. Self-regulation of a displayed EEG signal feature is the focus of the traditional biofeedback approaches; biofeedback training protocols on frequency bands 12-15 Hz and 15-18 Hz led to significant control over the corresponding rhythms compared to a non-trained control group (Egner and Gruzelier, 2004). The short term role of feedback was assessed by removing the feedback from random trials in an experiment where a cursor was controlled with mu-rhythm activity (8-12 Hz); the control ability was retained without the feedback and thus unaffected by the feedback (McFarland et al., 1998). With continuously presented visual feedback, in course of several sessions, subjects achieved average accuracies of 95%; instantaneous feedback can thus enhance classification accuracy (McFarland et al., 1998).

The two main strategies during subject training and learning with feedback are operant conditioning and predefined imagery instructions. Imagery strategy focuses on instructing the subjects to imagine specific motor movements or non-motor tasks, such as object rotation, for which the responses detectable and well-known. The focus of operant conditioning strategy is in achieving the control regardless of the actual source of control; the actual mental tasks performed by the subjects, however, vary greatly. The voluntary control with both strategies in the optimal case should, nevertheless, become unconscious and fully automatic. (Curran and Stokes, 2003).

Feedback is mostly presented to the user through the visual modality (Wolpaw et al., 2002). The other possibilities include auditory and haptic (tactile) feedback. Haptic feedback discrimination ability was evaluated in a study presenting tactile icons with varying rhythm and roughness to the subjects; subjects achieved overall recognition rate of 71%, and a rate of 93% for rhythm discrimination (Brown et al., 2005). The learning speeds with auditory and visual feedback modalities for BCI were compared in two multimodal feedback studies: the results with auditory feedback were significantly worse than with visual feedback (Hinterberger et al., 2004; Pham et al., 2005). A preliminary study comparing visual and haptic feedback for BCI concluded that with both modalities the learning speed was equal; both haptic and visual feedback could thus be equally used in giving feedback (Kauhanen et al., 2006).

Motivation affects the effectiveness of learning; internally motivated (self-motivated) individuals learn faster and have greater possibility to achieve control than individual requiring external motivation such as rewards. In the theory of locus of control of reinforcement (LOC), individuals with internal LOC evaluate the feedback through their performance or personality, and individuals with external LOC consider the feedback as good or bad luck, or destiny, independent of the individual's own performance. Seventeen novice subjects without previous BCI experience participated in a experiment; those with strong internal LOC could perform better with the BCI than those with ordinary LOC. (Burde and Blankertz, 2006).

1.3.3 Imagery

Imagery strategies are a common way to induce control over ones brain activity; the well-studied motor imagery, for instance, produces activations over the motor cortex (Pfurtscheller and Neuper, 2001; Neuper et al., 2005; Lotze and Halsband, 2006; Curran and Stokes, 2003; Jeannerod and Frak, 1999). Imagery is considered as training of brain areas involved in particular tasks; the resulting action is prevented at some cortico-spinal level (Pfurtscheller and Neuper, 2001). In addition to motor imagery, other mental tasks have also been used in BCI control; the Cooper-Shepard mental rotation task in particular has been, however, related to motor processes (Wexler et al., 1998).

Motor imagery can be described as conscious processing of movement intention; the brain areas for execution and planning are highly overlapping, and reactions of autonomous systems are similar to execution of real motor movements (Lotze and Halsband, 2006). Significant improvements can be achieved by training athletes and musicians with motor imagery; professionals often use more imagery than amateurs. Motor imagery can also be defined as the simulation process of an action within the brain (Decety, 1996). Even increases in muscle force are possible with mental training and imagery, without any muscle activations. On the other hand, brain-damaged patients are unable to imagine actions requiring the damaged parts of the brain; patients with Parkinson disease and brain lesions exhibit deficits in both real and imagined movements in the affected regions (Decety, 1996).

The imagined movements can be experienced in first person or third person perspective; first person perspective corresponds to kinesthetic imagery and the third person perspective to visual imagery (Decety, 1996). Kinesthetic motor imagery induced brain activity has been shown to be more distinguishable from background brain activity than visual imagery (Neuper et al., 2005), and kinesthetic imagery has been shown to better modulate corticomotor excitability than visual imagery (Stinear et al., 2006). Thus imagery strategies should focus on kinesthetic experience of motor imagery.

1.3.4 Machine vs. human learning

Two rough categories of BCI systems exist; the BCIs in the first category rely mainly on machine learning, neglecting the human counterpart (VEP, P300); and the BCIs in the second category depend mostly on the learning ability of humans to control and self-regulate signal features (SCP, SMR, RP). Both of these approaches suffice for BCI use; the inability of one independent system to adapt to another, however, may create an upper limit on the combined performance of the systems; these systems are also susceptible to non-stationarities in either of the systems. Similar limitations can result from different learning speeds and learning cycles of two adaptive systems, and biased estimates caused by recursive feedback loops. An assumption of continuous increase in performance during training with feedback does no longer hold; upper performance limit of 80% is sometimes reached after several sessions of training (Pfurtscheller and Neuper, 2001). Mutual learning of the two systems, human and machine, is therefore essential for successful BCI operation (Wolpaw et al., 2002; Millan Jdel and Mourino, 2003).

1.4 BCI applications

The purpose of brain-computer interfaces is to create a communication channel to an application, which would help the user to accomplish tasks without a caregiver. These applications are specific to different user groups and the level of assistance is also very different. This section reviews the current direction in the field on these issues and summarizes current trends in application research and development.

1.4.1 User groups and their needs

Discussions held at the Third International BCI meeting in Albany, NY, June, 2006, concluded that potential BCI users would be patients with severe progressive or non-progressive disabilities: those suffering from diseases, injuries, or functional impairments, or being completely locked in (Kübler et al., 2006). An important group without any residual communication capabilities are the individuals with total motor paralysis, caused most frequently by the late stages of amyotrophic lateral sclerosis (ALS) (Kübler et al., 2006). The primary goal of the BCI system is to provide patients means to express their needs to their caregivers and improve the quality of their everyday life. The ultimate goal of the research is to relieve the patients of constant need of help and to provide independent control of their own environment (Wolpaw et al., 2002; Kübler et al., 2006).

Other groups benefiting from BCIs are those needing another communication channel in addition to available ones which might be blocked for some other use; it has applications in military, transportation, space navigation etc. The entertainment sector, including gaming, video and music industries, could also benefit from brain-computer interfaces. For all user groups, inexpensive, reliable, and efficient BCIs are needed; EEG-based BCIs are currently closest to meeting the requirements and in addition have the ability to work in most environments (Wolpaw et al., 2002).

1.4.2 BCI as a part of assistive systems

Typical BCI applications provide basic communication capabilities: a 'yes-no' answering program, spelling programs, and a text writing program. A BCI system can also restore a patient's mobility and movement of the extremities: hand grasping is realized with a prosthetic device or with functional electrical stimulation. (Pfurtscheller et al., 2000, 2005), and transportation is made possible with an intelligent wheelchair or a robot (Millan Jdel et al., 2004). Various applications, like robotic arms and spelling programs, can be connected to a BCI with stable and universal control signals (Hochberg et al., 2006). A real-time computer game was also integrated with a BCI (Mason et al., 2004).

Although high accuracies over 90% can be reached with two-class BCIs based on self-regulated brain activity, the control of the applications can be inherently difficult because of errors and low information transfer rates; increasing the number of classes increases the information transfer rate but requires efficient classifiers to reach equivalent information transfer rates in two-class classifiers. To alleviate the problem the assistive systems have be designed to minimize the needed information transfer rate, and to maximize the adaptation of the application to the user's behavioral patterns. One way of ITR minimization is to reduce the amount of required choices by finite state automaton of high level commands (Millan Jdel et al., 2004); A mobile robot executes smooth turns, and enters rooms, according to the current command, until the next mental state changes the command. Maximum adaptation is sought in the writing program, DASHER, where selectable groups of letters can be optimized according to the user language and the list of mostly used words (Wills and MacKay, 2006). In shared autonomy the balance between human and machine control is adaptively altered according to the capabilities (ITR) and alertness of the user; the wheelchair can be in complete control of the user or a selected level of assistance could be given, including obstacle avoidance and autonomous navigation to a designated goal (Nuttin et al., 2001).

1.4.3 Current trends in research and applications

The focus is moving into developing brain-computer interface devices, which could be used and maintained in home environment with relative ease by non-expert caregivers (Kübler et al., 2006). To verify the applicability and usefulness of the BCIs to patients, larger patient populations should be used in experiments conducted in home or hospital environments. To speed up BCI system development in laboratories, a general purpose BCI software, BCI2000, was developed (Schalk et al., 2004). In spite of growing interest in invasive studies, most BCIs in future will still be based on the scalp-recorded EEG (Birbaumer, 2006). The motivation and the psychological condition of the patient greatly influence the performance and usefulness of the BCI operated application: identifying potential users requires screening procedures (Kübler et al., 2006). A recent study surveyed the ability of 99 healthy, novice volunteers to control a BCI in a short 20–30-minute, 2-session experiment; 93% of the volunteers achieved accuracies above 60%, indicating wide-ranging BCI operating capability in general population (Guger et al., 2003). The overall goal of the research is the improvement of the BCI hardware and software systems, improving the bit rates of the BCIs to enable the control of increasingly complex devices, and the improvement of the patients' quality of life (Cincotti et al., 2006; Sykacek et al., 2004).

Chapter 2

Methods

The experiment was designed to enable comparison of haptic and visual feedback during BCI training. The subsequent section describes the experimental setup, the classification methods, and the TKK BCI system, which was used in the experiments.

2.1 Experimental setup

Six right-handed 22- to 26-year-old able-bodied subjects (one female) with no previous experience of BCIs participated in the experiment.

EEG was recorded at 13 locations over the sensorimotor cortex (Figure 2.1) with the BrainProducts 32 channel active electrodes system combined with BrainProducts BrainAmp amplifier (http://www.brainproducts.com). The electrodes on the cap comprised built-in amplifiers, impedance level indicators, and active electromagnetic shielding. The sampling frequency was 500 Hz, and the reference electrode was situated between Fz and Cz. The signals were filtered in the amplifier with a band-pass filter between 0.1 and 250 Hz.

Subjects were seated comfortably in an acoustically and electrically shielded room, facing a monitor that displayed a simulated wheelchair from above (Figure 2.2). The wheelchair was autonomously controlled in a maze by a computer while the subjects controlled the

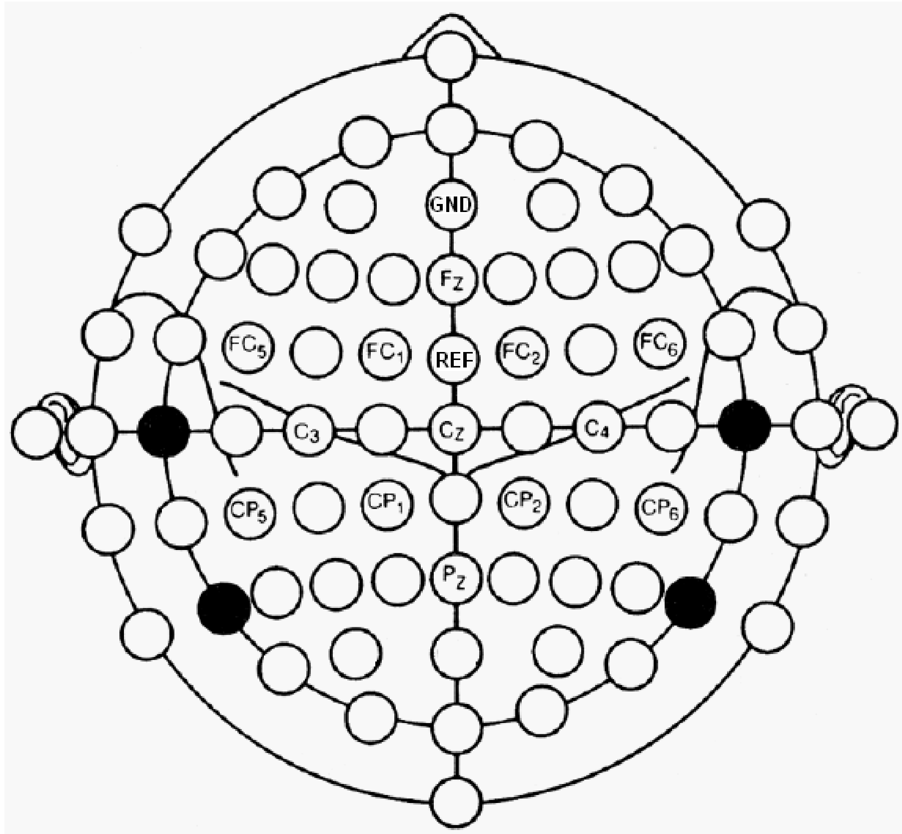

Figure 2.1: The positions of the 13 EEG electrodes over motor cortex. Reference was situated between Cz and Fz and ground in front of Fz. The electrodes locations on the cap were in accordance to the international 10-20 system. Adapted from ACNS (2006).

BCI; the purpose of the maze was to distract the subject and also to make the current task predictable (Figure 2.3). A red task indicator was situated adjacent to the wheelchair. The maze, where the wheelchair navigated, was an infinite circular corridor with obstacles requiring left and right turns.

The red task indicator was displayed in left, right, or upward position (Figure 2.4): in left and right positions, the subject's task was to imagine continuous, kinesthetic movements of the respective hand. They were allowed to relax, move, and blink eyes in the upward position, and prepare for the following movement. The tasks were predictably changed online by the experimenter from left task to right task, going trough upward task, and in reverse order. Each left and right task lasted 5 to 10 s and each upward task lasted 1 to 2 s. The left and right tasks were alternated by experimenter to approximately match the path taken in the environment by the wheelchair.

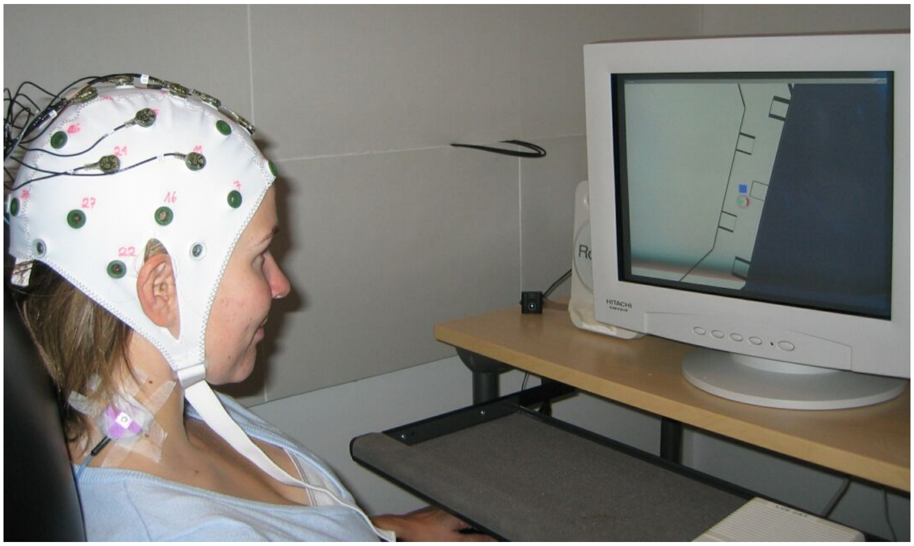

Figure 2.2: Subject sitting comfortably in front of the screen displaying the wheelchair simulator. The subject receives visual feedback through the screen and haptic feedback with the vibrotactile elements placed on both sides of the base of the neck. The subject is wearing the BrainProducts ActiCap with the 13 electrodes attached to the cap.

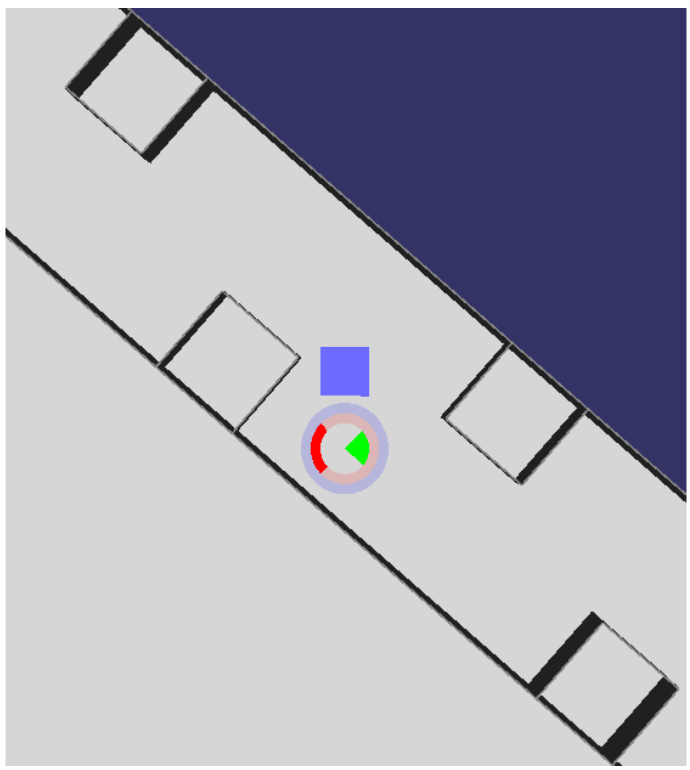

Figure 2.3: Top view of the wheelchair simulator program. The red task indicator and the green visual feedback are displayed below the blue-colored robot. The wheelchair navigates in an infinite corridor with obstacles.

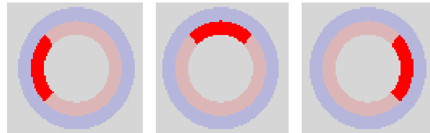

Figure 2.4: The red visual targets to the left, up, and right, displayed adjacent to the wheelchair in the simulator program window. The experimenter had the possibility to change the direction of this indicator at will using the keyboard.

The experiment consisted of nine 4.5-minute sessions (Figure 2.5). The first session included no feedback. Both feedback modalities, haptic and visual, were presented simultaneously in sessions 2 and 3 to familiarize the subjects with them. Subjects S1-S3 received haptic feedback in sessions 4 to 6 and visual feedback in sessions 7 to 9. For subjects S4-S6 the order of the feedback modalities was reversed. Short breaks were kept between sessions.

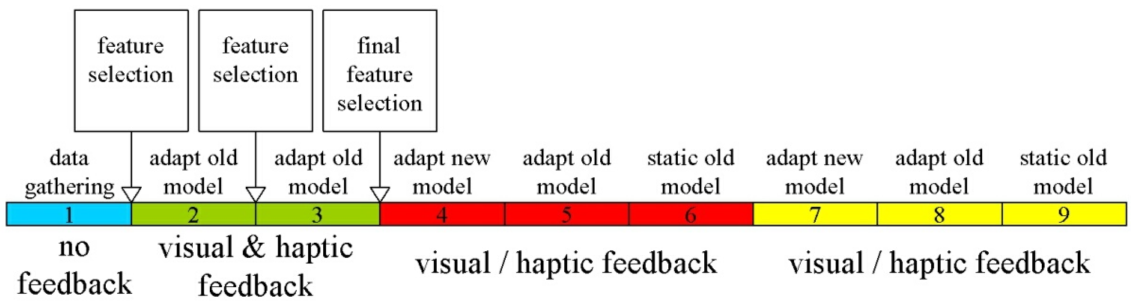

Figure 2.5: The experiment session structure. The experiment consisted of nine 4.5-min sessions. The first feature selection was based on the first session, in which the subject received no feedback. The second feature selection was based on the data of second session and the final feature selection on the data of second and third sessions; the subject received both feedback modalities in those sessions. The order of haptic and visual feedback modalities was chosen for sessions 4 to 6 and 7 to 9 before the start of the experiment.

In sessions 2-9, the subject was given visual or haptic feedback or both once every second; the class probabilities of the newest features determined the direction of the feedback. The visual feedback was displayed with a rose, a circle divided horizontally and vertically into four equal sectors, in the middle of the simulator screen with a green segment in each of the four directions. The left and the right segments appeared for 200 ms depending on the output of the classifier (Figure 2.6). The haptic feedback (vibrotactile stimulation) was given for 200 ms at 200 Hz with the EAI C2 device (www.eaiinfo.com) with detachable vibrating elements attached with tape to the left and right side of subject's neck, above the neck-shoulder junction (Figures 2.2, 2.7).

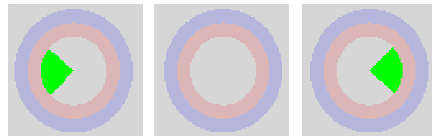

Figure 2.6: The green visual feedback displayed adjacent to the wheelchair in the simulator program window. The green sector was visible in one direction for 200 ms once every second during visual feedback sessions.

Figure 2.7: The detachable haptic (vibrotactile) feedback element, which was attached with tape to the left and right sides of the base of the subject's neck. The elements generate vibration by electromagnetically moving a block inside the element.

2.2 Classification

Motor planning, execution, and self-regulation of imagined motor movement typically display rhythmic behavior in the mu- (8-12 Hz), beta- (18-26 Hz), and intervening bands. The rhythmic activity resulting from motor imagery was assumed to be contained within the 8-30 Hz range. One instantaneous spectral power value was used as a feature for each EEG channel. The rhythms vary between subjects and the most predictive frequency bands are not known prior to the experiment. We used a feature selection algorithm to find optimal features for each subject.

The features were calculated once every second by convolving the EEG signals in each channel with Gabor filters. The definition of the Gabor filter is

$$w(t,\ f_c) = A \exp{(\frac{-t^2}{2\sigma_t^2})} \exp{(j 2\pi f_c t)}, \tag{2.1}$$

where t is the time position within the filter, f_c the center frequency of the filter, A the amplitude normalization coefficient, and σ_t is the scale of the filter in time domain.

The scale of the filter in frequency domain is given by

$$\sigma_f = \frac{1}{2\pi\sigma_t}, \tag{2.2}$$

characterizing the tradeoff between time and frequency resolution. The time scale of all filters was set to $\frac{1}{\pi}s = 0.3183s$ and the lengths of the filters were limited to 2s.

We used a linear model as a classifier with a logistic output function (Bishop, 1995), given by

$$p\left(t^{(n)} = 1|y^{(n)}\right) = \frac{1}{1 + \exp\left(-y^{(n)}\right)}, \tag{2.3}$$

where $p\left(t^{(n)} = 1|y^{(n)}\right)$ is the model of the probability for class $t = 1$ given feature vector $\mathbf{x}^{(n)}$ and parameters $\mathbf{w}$. $t^{(n)}$ indicates class membership and can have integer values [0 1]. and $y^{(n)}$ is the corresponding latent variable related to sample (n). $y^{(n)}$ is given by

$$y^{(n)} = \mathbf{w}^T \mathbf{x}^{(n)}, \tag{2.4}$$

where $\mathbf{w}$ is a vector of model parameters, weights and $\mathbf{x}^{(n)}$ is the sample vector (n).

The classifier parameters were updated online once every second with the iterative least squares algorithm (McCullagh and Nelder, 1989). A prediction of the current class was made once every second for the newest sample before retraining of the model; a maximum of 300 most recent samples ($\sim$5 min of data) with correct class labels was used as training data for each class.

In feature selection, subject-specific center frequencies f_c, as well as the influence of each channel on classification result, were determined using Bayesian inference. Markov Chain Monte Carlo (MCMC) methods were used to draw samples from the joint posterior distribution of the model weights $\mathbf{w}$ and input features $\mathbf{x}^{(n)}$ (Jylänki et al., 2006). Instead of sampling the parameters of the linear model directly, a Gaussian process prior was constructed for the outputs of the linear model, i.e., the latent variables $y^{(n)}$ (Rasmussen and Williams, 2006). MCMC sampling was done by repeating three steps. Hybrid Monte Carlo (revised in Neal, 1996) was used to sample the latent variables given input features. Given the latent variables, the centre frequencies f_c were sampled with Slice sampling (Neal, 2003). Reversible Jump Markov Chain Monte Carlo (RJMCMC) was used to jump between models with different input feature combinations (Green, 1995). The linear model was treated as a Gaussian process, i.e. the parameters of the linear model were integrated out, to facilitate the sampling of Gabor frequencies and the jumps between different input configurations. As a criterion for selecting features, we required a given channel and the corresponding center frequency f_c to be included in the model with sufficiently high posterior probability; we chose six or more of the most probable features for which the joint probability exceeded 0.25.

The feature selection was done during the breaks after sessions 1 to 3 (Figure 2.5). After sessions 1 and 2, the best center frequency f_c for each channel was determined based on the data from the previous session. In sessions 2 to 3, the subject-specific center frequency f_c from each of the 13 channels was included in the model and the model was trained with data from the previous session. After session 3, using data from sessions 2 to 3, the sampling of input channels was combined with the sampling of the center frequencies, f_c, to determine the final features. With the final features we initialized a model, which then was used in sessions 4 and 7. The model was trained online in sessions 2-5 and 7-8 (Figure 2.5). The model was tested, without any additional training, in sessions 6 and 9. The classification results were saved in a confusion matrix (see example in Table 2.1), which describes the amount of correctly and incorrectly classified single trials of the individual tasks.

Table 2.1: An example of a confusion matrix. Single trial results for a task are added to corresponding elements of the matrix. The elements in the matrix diagonal indicate the number of single trials that the subject was able perform correctly. Overall performance (accuracy) can be calculated by dividing the sum of the diagonal elements with sum of all elements. In the example the overall accuracy is 88.9%.

		Classification Result	
		Left	Right
Task	Left	101	20
	Right	7	116

2.3 TKK BCI system

The BCI system (Figure 2.8) comprises the ActiCap BrainProducts 32 channel active electrode System, the robot simulator program, the haptic device, Matlab®for signal processing and the graphical user interface, and the main C/C++ control program for integration and experimenter control. The BCI system runs on a PC with Windows XP.

The Vision Recorder software (Figure 2.9) receives amplified signals from the EEG measurement device; various settings including filtering settings and recorded channels can be changed within the Vision Recorder program. BrainProducts provides a TCP/IP server for the Vision Recorder, which enables data transfer to other programs; in this case the main control program connects to the TCP/IP server and continuously retrieves the data from the Vision Recorder server. The Vision Recorder and signal acquisition needs to be started before the main control program.

The robot simulator displays a wheelchair navigating in a simulated environment, cues (tasks indicators), and visual feedback to the subject (Figure 2.10); the simulator and a TCP/IP command interface were designed and created by the Department of Mechanical Engineering, KU Leuven, Belgium. The simulator accepts steering and goal commands through TCP/IP from the main control program. The simulator also needs to be started before the main control program. The main control program also controls the haptic device. The haptic device (EAI C2 -device with 8 vibrotactile elements) is connected to the PC with a USB cable and is operated through a virtual communications port with a

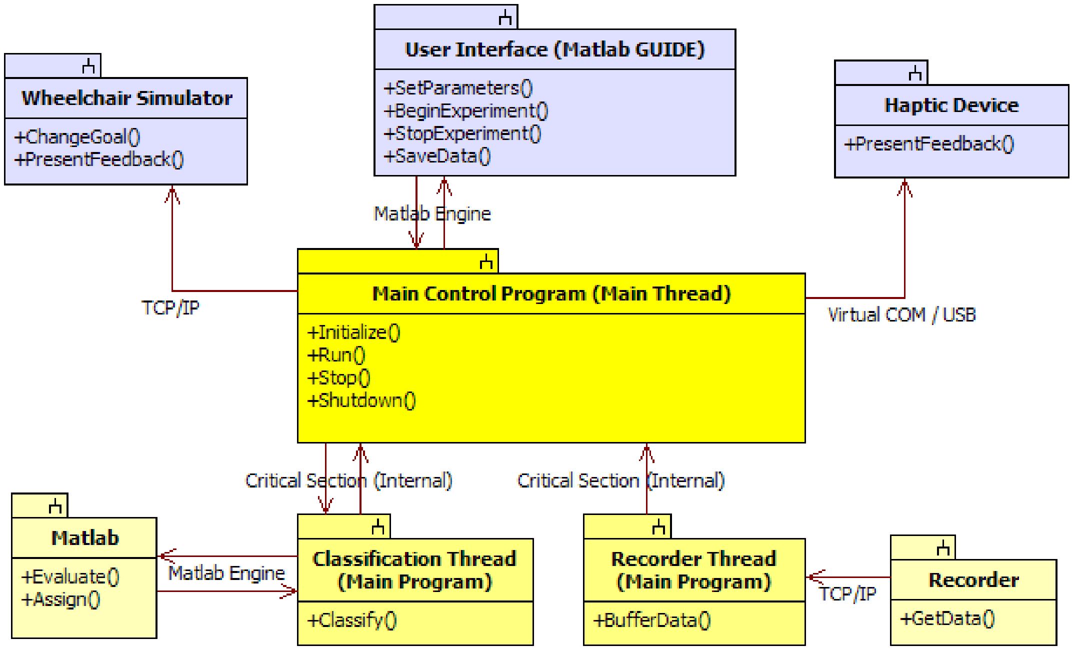

Figure 2.8: A schematic overview of functional relation and operation of the TKK BCI. The parts of the program are the main control program, the user interface, the simulator, the haptic device, The MathWorks Matlab®, and the Vision Recorder. There is either one-directional or bi-directional data flow between the system parts. The functions listed for each of the parts are only for illustration of the functionality.

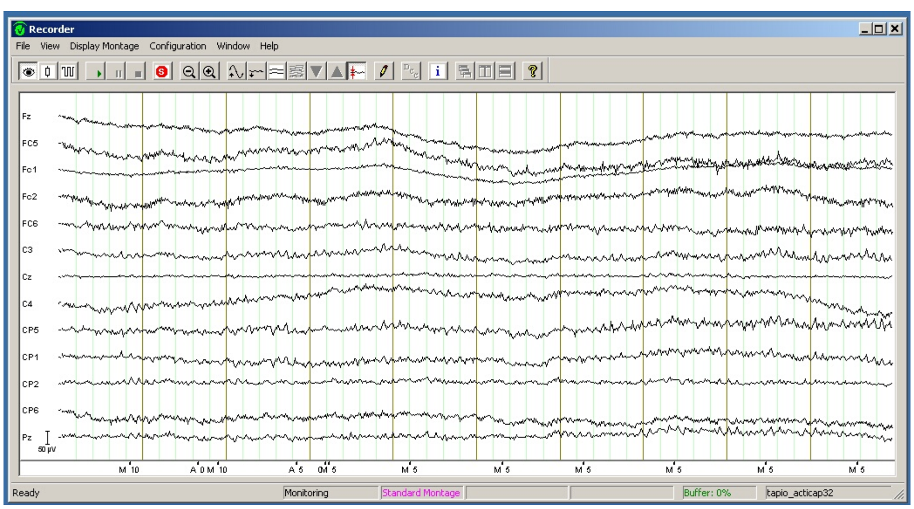

Figure 2.9: The visualization window for EEG data in the Vision Recorder software. Each channel is presented on separate rows with the name and the scale of that channel; the scale of the channels and the set of channels can be changed to more suitable if required. Triggers from other programs through an interface on the data acquisition card appear on the bottom of the EEG screen as tick marks with a letter and a number.

custom driver (COM -port). Parallel port communication is also available for sending additional triggers to, for instance, Presentation®(Neurobehavioral Systems).

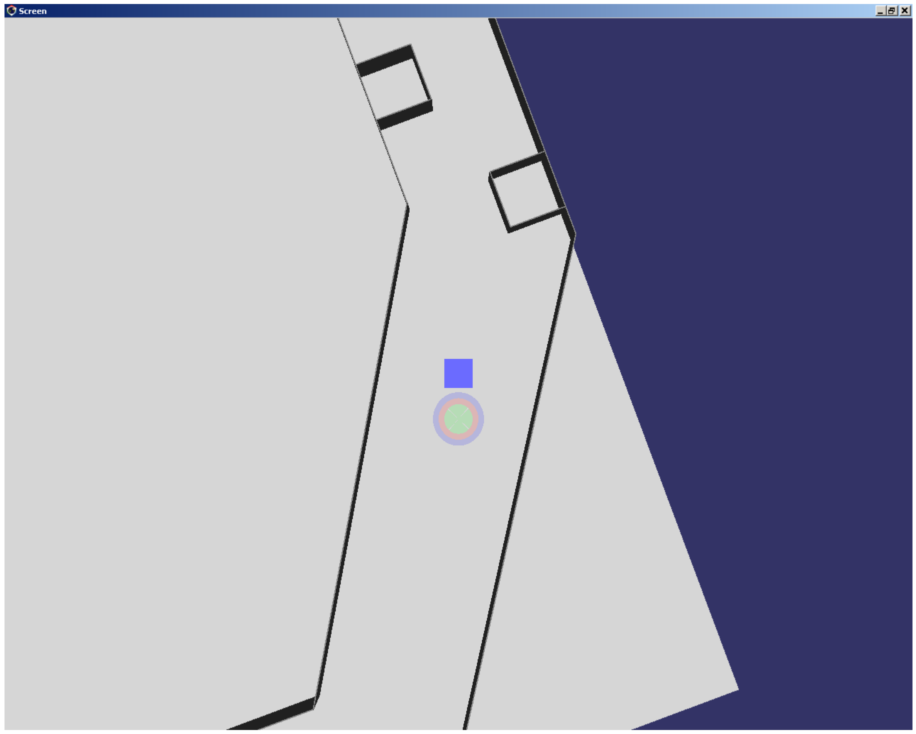

Figure 2.10: A top view of the simulator program window; the combined task indicator (red) and visual feedback (green) element is located below the wheelchair (blue) in the window. The window opens to full screen in the monitors located in the measurement room and the EEG control room.

Matlab®(The MathWorks) handles both the signal processing capabilities and the graphical user interface (GUI) of the BCI system through a Matlab®Engine -connection. Matlab®offers flexibility in the implementation of the signal processing algorithms; the flexibility allows preprocessing of the signals with combinations of various custom algorithms, and classification with a set of linear and non-linear classification algorithms. The graphical user interface (Figure 2.11) is based on Matlab®Guide framework with built-in windowing and event handling environment; the subject information management and experiment control systems were implemented with necessary functionality. The most important settings affecting the experiment can be changed through the Matlab®GUI, including the type, the duration, and the frequency of the feedback. The Matlab®GUI initializes a model structure, which consists of the parameters of the classifier and all experiment parameters including the subject information. The model is saved after each session with the EEG data in Matlab®format and can be reused and trained further in later sessions.

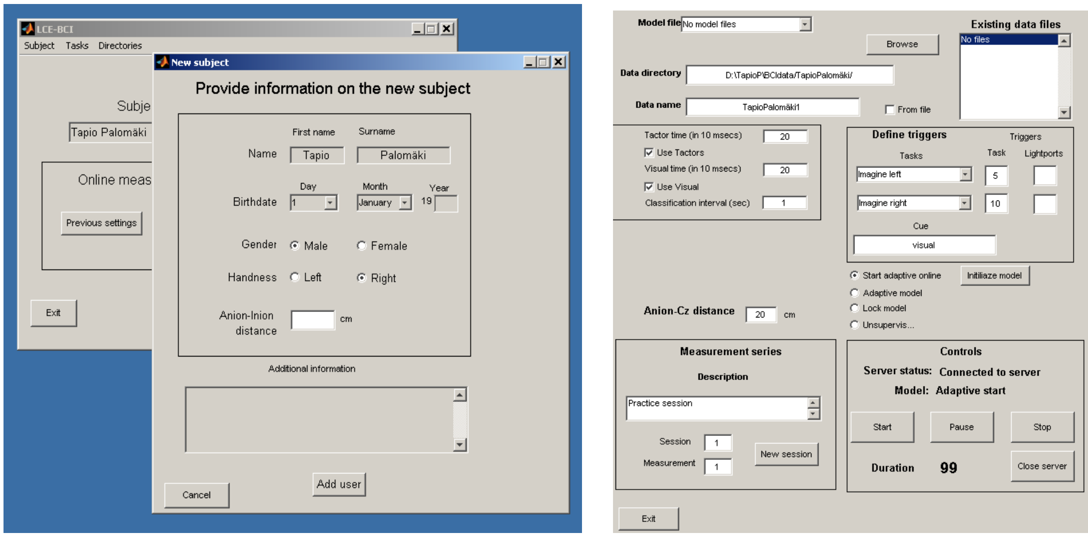

Figure 2.11: The graphical user interfaces (GUIs) for subject management and experiment control. The subject management window (left) allow for inputting the name, the age, the gender, the handedness, and the anion-inion distance of each subject to be stored along with other experiment information. The experiment control window (right) allow the changing of the type and the length of the feedback, and the settings of the classifier model, such as adaptation settings and the base model. The start and stop buttons control the start and end of a session in the experiment.

The main control program is implemented with C/C++ programming language and its functionality is customized for BCI purposes. The program provides a multi-threaded environment for simultaneous, asynchronous communication with the other parts of the systems. The keyboard of the PC is directly connected to the main control program, for instance for giving new instruction or goals to the subject. The remaining settings can be changed within the user interface of the program before and after an experiment; several infrequently changing hardware related settings and program logic can be modified in the program source code.

The main control program consists of three threads (Figure 2.8), one main thread for program execution and peripheral device control (simulator and haptic device), one thread for data acquisition from Vision Recorder through TCP/IP, and one thread for signal processing and classification in Matlab®through Matlab®Engine connection. The first thread, the main thread, initializes all device connections and the other threads, starts the graphical user interface, and then waits for further commands and messages from other threads.

The main thread sends commands to the simulator based on periodic classification results from the classification thread; the same commands can also be sent to the haptic device. The selections of feedback modalities by experimenter among other settings are read from the GUI into the main control program in the beginning of every session. These settings are available for customizing session settings in the C/C++ code without requiring the recompilation of the source code.

The second thread, the data acquisition thread, continuously retrieves new signal data from TCP/IP server of the Vision Recorder software; new data are available every 10 or 20 ms, depending on configuration of the Vision Recorder. Each EEG-channel in Vision Recorder is stored in two matrices, which hold the unused recent data and a previous history of data from a fixed time period; these buffers are stored in Matlab®workspace and passed as parameters of the classification function. The matrices are persistent and the contents of them can be changed during the classification function call. The thread is also able to read and store markers (triggers) from Vision Recorder, enabling external triggering and time-locking. All EEG data (including the markers, timing information and task labels) is also saved to files in local hard drive in Matlab®and Vision Analyzer formats for later offline analyzing (in addition to saving the data manually in Vision Recorder).

The third thread, the classification thread, connects to Matlab®with Matlab®Engine and periodically transfers buffered EEG signal data to Matlab®. Matlab®executes an user-defined online_classification_adapt() function with the EEG signal from all channels and other classification related parameters, such as current task; The signal data comprises all the channels selected in the workspace of the Vision Recorder program. The function returns the classification result and the certainty of the result. The first thread reads those classification results and sends the corresponding steering and acceleration commands to the wheelchair simulator, and the feedback commands to the haptic device.

Chapter 3

Results

The following section describes the classification results and selected features for all subjects, and time-frequency representations and event related potentials of the responses to haptic stimulation for one subject.

3.1 Classification

The classification accuracies for left and right motor imagery are shown in Figure 3.1 for the six subjects during the training with haptic and visual feedback; on average there were 206 classifications during each individual session. The overall accuracy for left and right hand imagery discrimination of each individual session was calculated using the correctly and the incorrectly classified trials in the confusion matrix. S1 obtained the best accuracy of 88.8% in session 7 with visual feedback; the average accuracy of all subjects in sessions 4 to 9 was 68%. S1-S3 received haptic feedback in sessions 4 to 6 and visual feedback in sessions 7 to 9; for S4-S6 the order was reversed. S6 did not exceed the accuracy of 60% during the experiment.

The average accuracies of each subject with haptic and visual feedback are presented separately in Table [2]. The average accuracies for both feedback modalities are close to

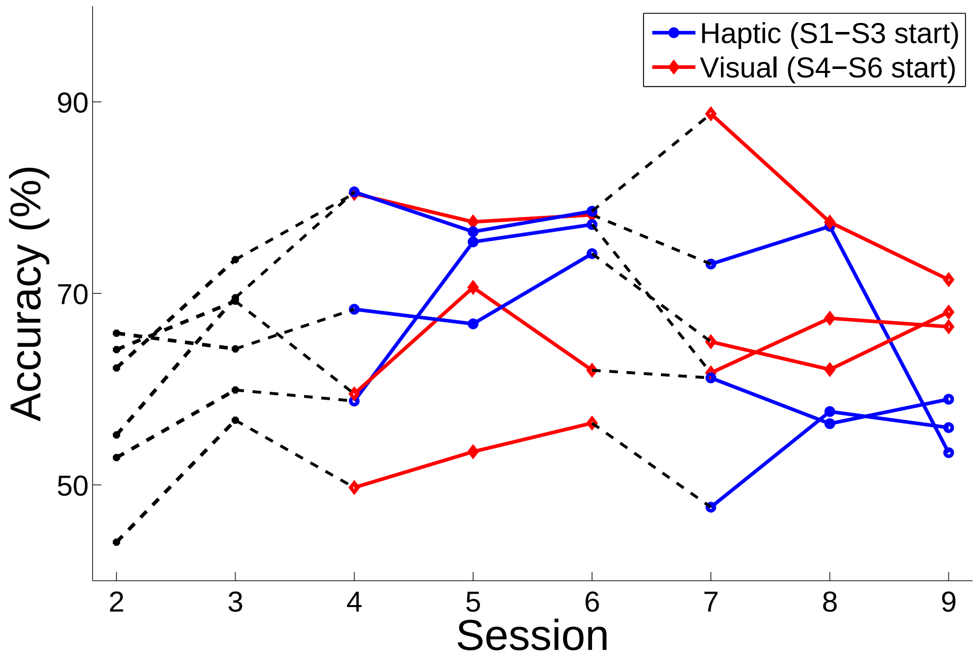

Figure 3.1: Individual subject performance (accuracy) during sessions 2 to 9, in which they received feedback. Sessions with haptic feedback are indicated with blue lines and sessions with visual feedback with red lines; familiarization sessions, 2 and 3, are indicated with thick dashed black lines. The thin black dashed lines connect the sessions of the individual subjects.

equal. S1 achieved the best average accuracies, 79% for both haptic and visual feedback. S4 was the second best, achieving 79% with visual feedback and 69% with haptic feedback. Sessions 6 and 9 were reserved for testing the classifier models with both feedback modalities without training them during the session. Table [3] shows these results for each subject with both feedback modalities. The average test results across subjects with haptic and visual feedback are also nearly equal, 66% for haptic and 67% for visual feedback. S1 achieved the best accuracy, 79%, with haptic feedback and S4 the second best, 78%, with visual feedback.

The average accuracies for S1-S3 and S4-S6 during the haptic or visual feedback sessions are displayed in groups in Figure 3.2. The results for haptic and visual feedback are similar for S1-S3 (72.9% and 69.8%, respectively); the results for haptic and visual feedback are also similar for S4-S6 (60.1% and 65.3%, respectively). The counterbalanced training, starting with either haptic or visual feedback, shows no advantage for training with

Table 3.1: Average performance for S1-S6 with haptic (HF) and visual (VF) feedback in sessions 4-6 and 7-9; S1-S3 received haptic feedback and S4-S6 visual feedback in sessions 4-6, with the feedback modalities changed for sessions 7-9. The average accuracies for haptic and visual feedback across all subjects are nearly equal, close to 68%.

	S1	S2	S3	S4	S5	S6	Mean ± SD
HF	79	70	70	68	59	54	67 ± 9
VF	79	65	65	79	64	53	68 ± 10

Table 3.2: Test session (sessions 6 or 9) performance for S1-S6 with haptic (HF) and visual (VF) feedback. The average accuracies for haptic feedback and visual feedback over all subjects are close to 67% and again nearly equal.

	S1	S2	S3	S4	S5	S6	Mean ± SD
HF	79	77	74	53	59	56	66 ± 11
VF	71	67	68	78	62	56	67 ± 8

either of the feedback modalities. There was high within-subject and between-subject variability in the individual sessions.

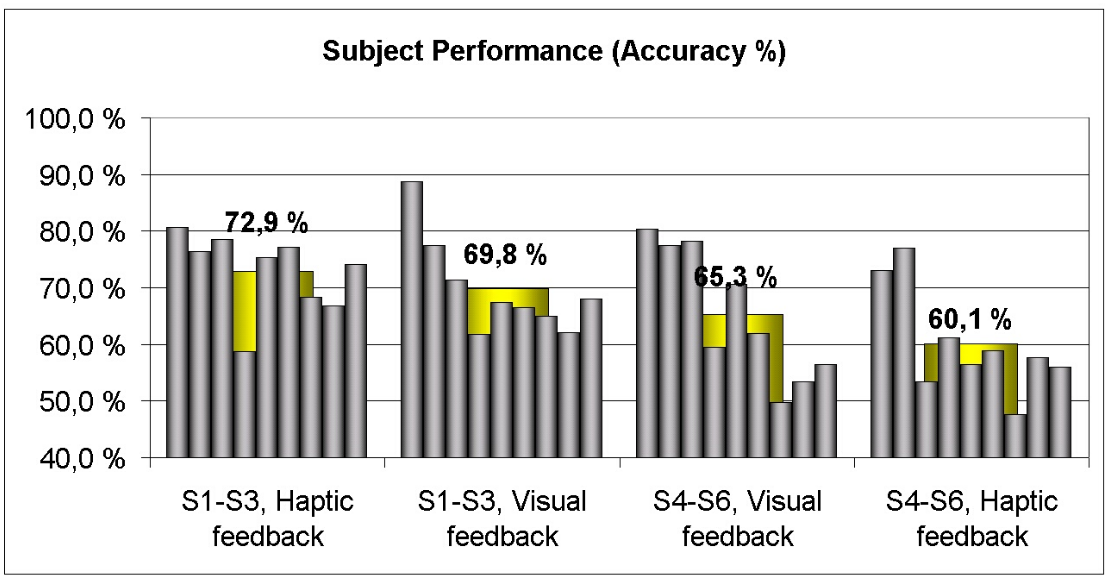

Figure 3.2: The accuracies for S1-S3 and S4-S6 in individual sessions when the subjects were receiving either haptic or visual feedback. Accuracies in individual sessions are presented in gray and average performances in yellow color.

3.2 Features

The selection of the final features (Table 3.3) with the Markov Chain Monte Carlo feature selection algorithm occurred after session 3 for each subject based on the data from sessions 2 and 3; the selected features were then used in sessions 4 to 9. The algorithm selected linearly the most separable features over the 13 electrode locations (channels) over sensorimotor cortex. Central electrodes over left and right hemispheres (channels C3 and C4) were selected for all subjects; otherwise the selected electrodes depended on the subject. The significance of the central electrodes Fz and Cz was low for most of the subjects. The most commonly selected frequencies situated within frequency bands 9-12 Hz and 19-24 Hz.

Table 3.3: The features selected after session 3 for each subject. A maximum of one frequency was selected for each of the 13 channels. The feature selection resulted in selection of channels C3 and C4 for all subjects; the frequencies on those channels were also mostly in mu -rhythm band (8-12 Hz).

	Fz	FC5	FC1	FC2	FC6	C3	Cz	C4	CP5	CP1	CP2	CP6	Pz
S1			12	9		24		12		24	23		12
S2	9	9			9	12		10	10	12		12	
S3			9		17	12		12	11		16		
S4		11	9	11	9	10	10	10		13		10	10
S5		29	9	9	22	19		14			21	12	20
S6		9	8			9		12	10	22		9	12

The average posterior probabilities of the electrode locations for each subject in sessions 4 to 9 are shown in Figure 3.3; the posterior probabilities were calculated for the best Gabor filter in each electrode location with the Markov Chain Monte Carlo feature selection algorithm. For half of the subjects (S1-S3) the most important electrode locations (channels) for classification in sessions 4 to 9 were C3 and C4 with high probabilities (85-97%). For S4 the most important channels were C3 and CP6 with probabilities 85 and 100%. The location and the distribution of the relevant electrode locations show variability for S5 and S6. Subjects with consistent electrode locations and features achieved better results compared to subjects with no consistent patterns of activations; S1-S4 with clear patterns achieved higher results than S5-S6. The best center frequency for S1-S3 was 11.5 Hz for channels C3 and C4; for S4 the best center frequency was 10 Hz for both C3 and CP6. The best center frequency varied greatly for S5 and S6 between 8 and 14 Hz; no best frequency can be identified. The center frequency of the best Gabor filter varied within 1 Hz even for the best channel for the best S1; for other subject the variability was greater.

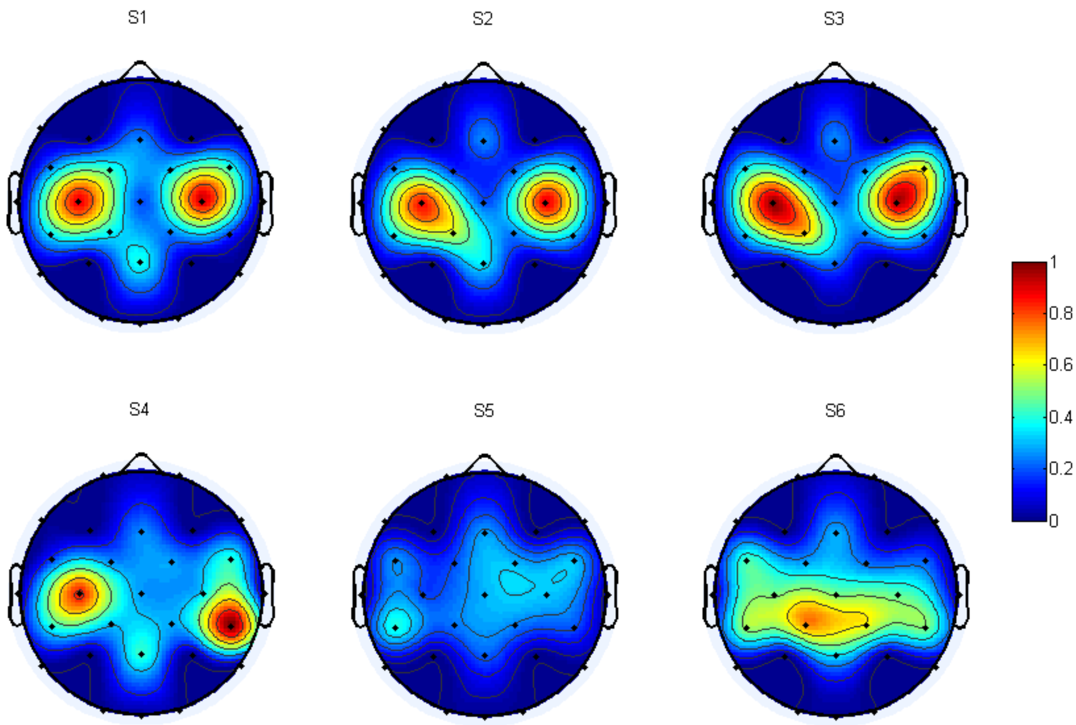

Figure 3.3: The average posterior probabilities of electrode location and one gabor filter during the 6 training sessions. Red and yellow colors indicate electrodes with high relevancy, and blue colors indicate electrodes with low relevancy.

The average time-frequency representations (TFR) of the channels with highest posterior probability in the feature selection algorithm are presented in Figures 3.4-3.9; one channel was selected in both hemispheres for each subject during left (top row) and right (bottom row) hand imagery. The TFRs were calculated with the same Gabor filter parameters as in the experiment. The filters were 2 s long and the center frequencies were placed 0.5 Hz apart from each other in the frequency band of 5 to 25 Hz. The trial windows were taken from the change of task to 8 s after the change from each session. We averaged 26-38 time-frequency representations for each subject either in haptic or visual feedback sessions; no trials were rejected prior to averaging. The figures for S1 (Figure 3.4) and S3 (Figure 3.6) were averaged using data from the three haptic feedback sessions; visual feedback sessions were used for average TFRs for subjects S2 (Figure 3.5), and S4-S6 (Figure 3.7-3.9). Haptic or visual feedback sessions were chosen based on the clearness of the resulting figures; the other figures not shown here show similar patterns.

The relative contribution of frequency components to the signal are shown in Figures 3.4-3.9; the red colors indicate higher contribution and the blue colors lower contribution of a frequency. Note different scales for the band powers for each subject. S1-S3 show desynchronization of the 11.5 Hz activity in the hemisphere contralateral to the imagined hand; during left hand imagery the band power decreases in the right (contralateral) hemisphere and correspondingly the band power decreases in the left (ipsilateral) hemisphere during right hand imagery. S4 shows similar desynchronization in the frequency band near 10 Hz and weaker desynchronization near 20 Hz during hand imagery. The 10 Hz, 11.5 Hz, and 20 Hz activity mostly remains in synchronized state in the hemisphere during ipsilateral hand imagery; the band power near the mentioned frequencies remains high. During the first two seconds after the task change for S1-S4 the activation in ipsilateral hemisphere slowly returns to synchronized state. We could not see any consistent patterns of activations for S5 and only weak patterns for S6. The consistency of the activation patterns directly correlates with the classification results; S1-S4 have clearly visible patterns and higher classification results than S5 and S6.

The non-averaged TFR of the activity in channel C3 and C4 for S1 are presented in Figure 3.10. During the period of 90 seconds the subject imagined left hand movements (red lines at the bottom of the pictures), right hand movements (blue lines), or did no specific task (black lines). During the left hand imagery the activity in the right hemisphere is desynchronized and the EEG band power near 11.5 Hz decreases; the band power returns to average during imagined right hand movements. This corresponds to the average activity seen in Figure 3.4. Similar activations can be seen in the other subjects.

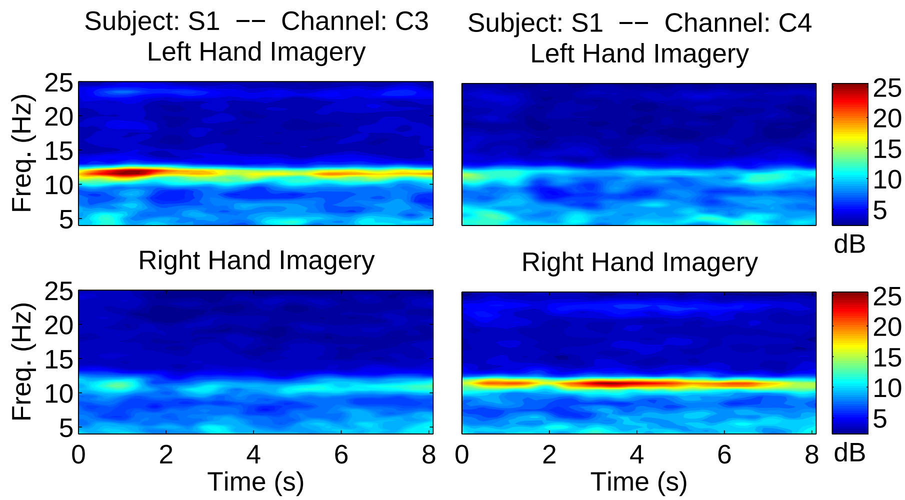

Figure 3.4: Average TFRs for S1 at channels C3 and C4, sessions 4-6 with HF.

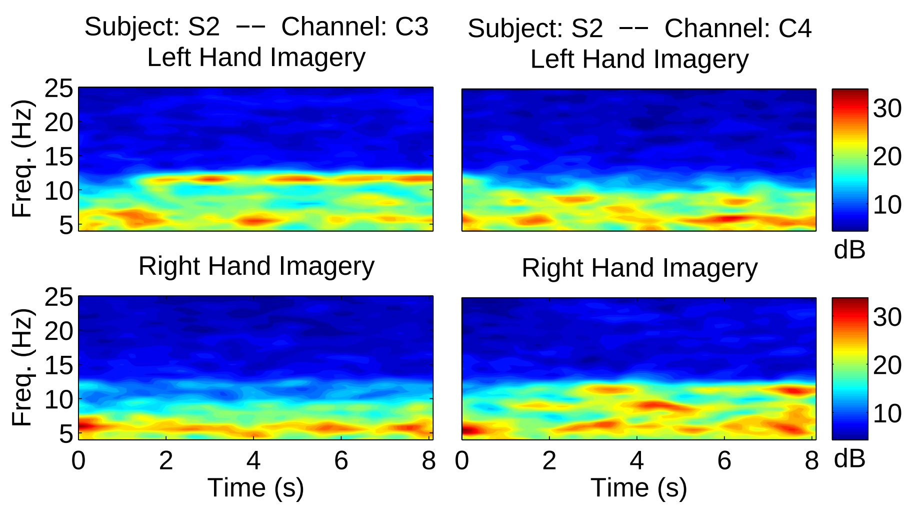

Figure 3.5: Average TFRs for S2 at channels C3 and C4, sessions 7-9 with VF.

3.3 Interference from haptic stimulation

We next wanted to see whether haptic feedback affects brain responses within the used frequency band. The average time-frequency presentation in Figure 3.11 shows the response to the haptic stimulation at the both sides of the neck, measured for S1 at electrodes C3 and C4. The figures were averaged over sessions 4 to 6, where the subject received haptic feedback on the left side (N=309) and on the right side (N=309); the TFRs were calculated time-locked to haptic stimulation (0 ms) and averaged after baseline correction with data from -300 to 0 ms relative to haptic stimulus onset. A response to the haptic stimu-

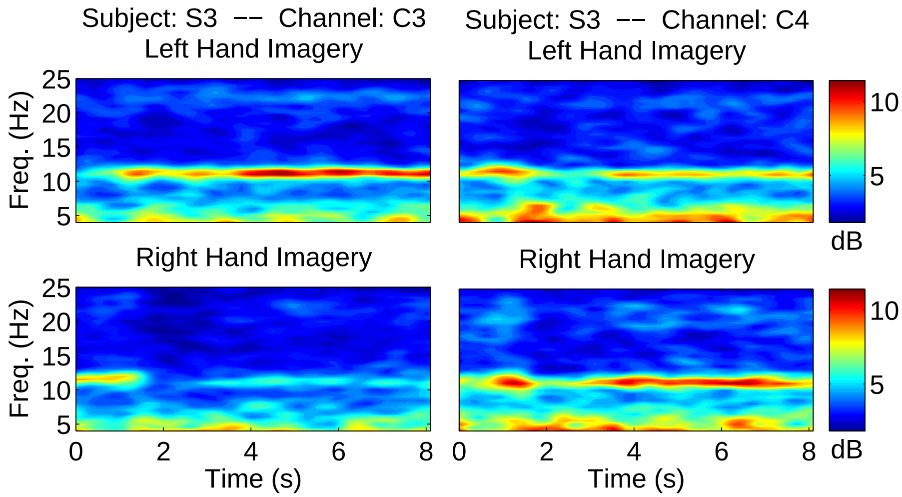

Figure 3.6: Average TFRs for S3 at channels C3 and C4, sessions 4-6 with HF.

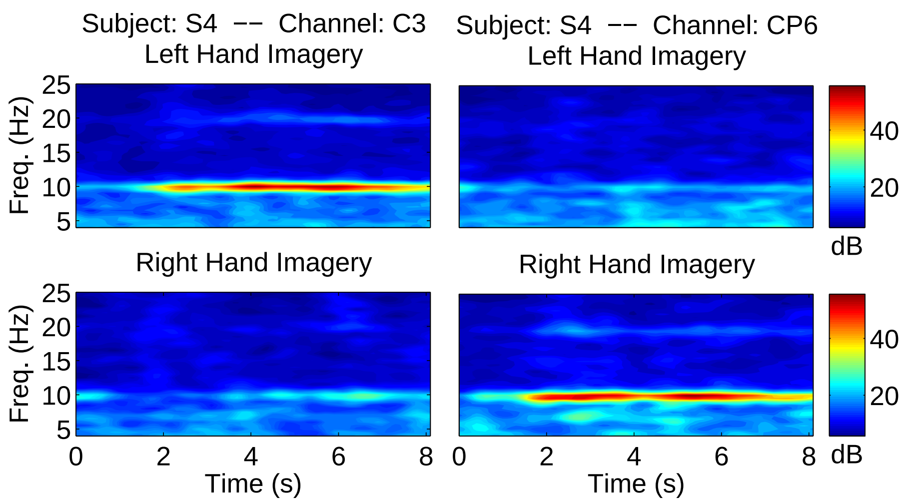

Figure 3.7: Average TFRs for S4 at channels C3 and CP6, sessions 4-6 with VF.

lation appears in 0-8 Hz and 30-40 Hz bands in synchrony with the onset and end of the haptic stimulation. Similar activation can be seen in all subjects. This response is outside the used frequency band 8-30 Hz.

Figure 3.12 displays the event related potentials (ERP) to haptic stimulation to the left (blue) and right (red) side for S1 at electrode locations C3 and C4, low-pass filtered below 10 Hz. The figures were averaged over sessions 4 to 6, where the subject received haptic feedback (N=309). A N200 peak can be seen in both hemispheres during left and right side vibrotactile stimulation. These peaks seen in ERPs have no role in real-time

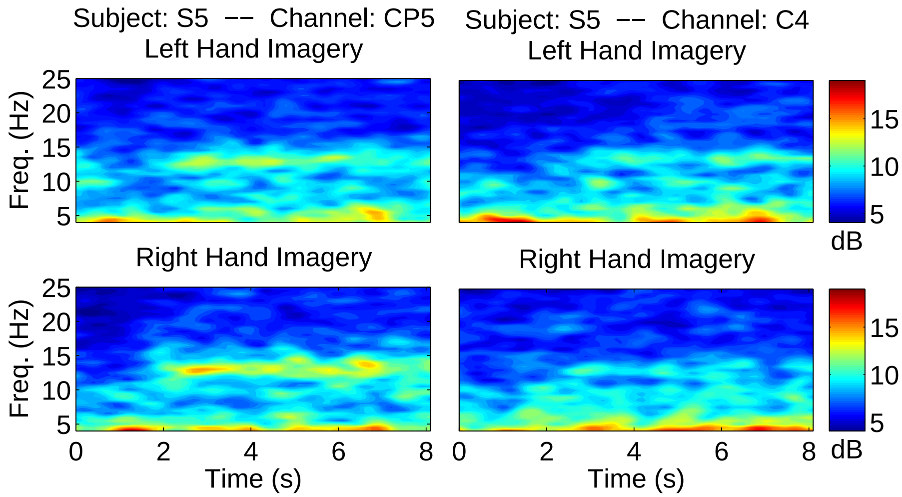

Figure 3.8: Average TFRs for S5 at channels CP5 and C4, sessions 4-6 with VF.

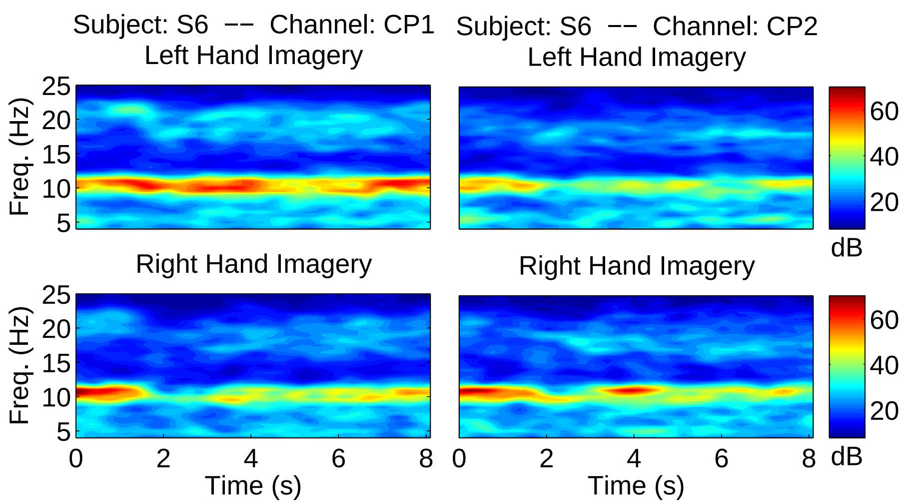

Figure 3.9: Average TFRs for S6 at channels CP1 and CP2, sessions 4-6 with VF.

classification using time-frequency transformations in the 8-30 Hz frequency range.

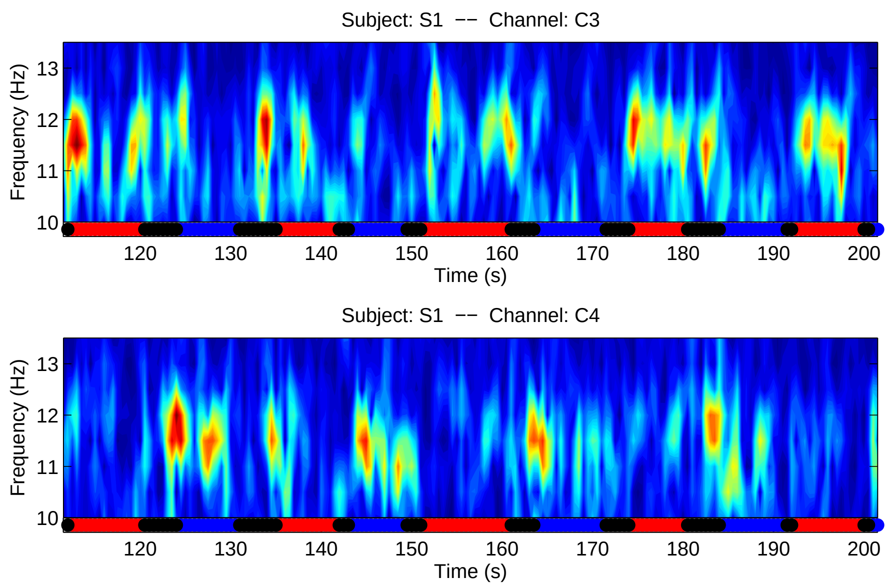

Figure 3.10: TFRs of S1 brain oscillations in 10 to 12 Hz band at C3 and C4. Bottom line of the pictures: the red lines indicate left hand imagery, the blue lines indicate right hand imagery, and the black line indicates no specific task. Decreased (desynchronized) band power is visible during left hand imagery (red lines) near the frequency of 11.5 Hz at C3 and at C4 during right hand imagery.

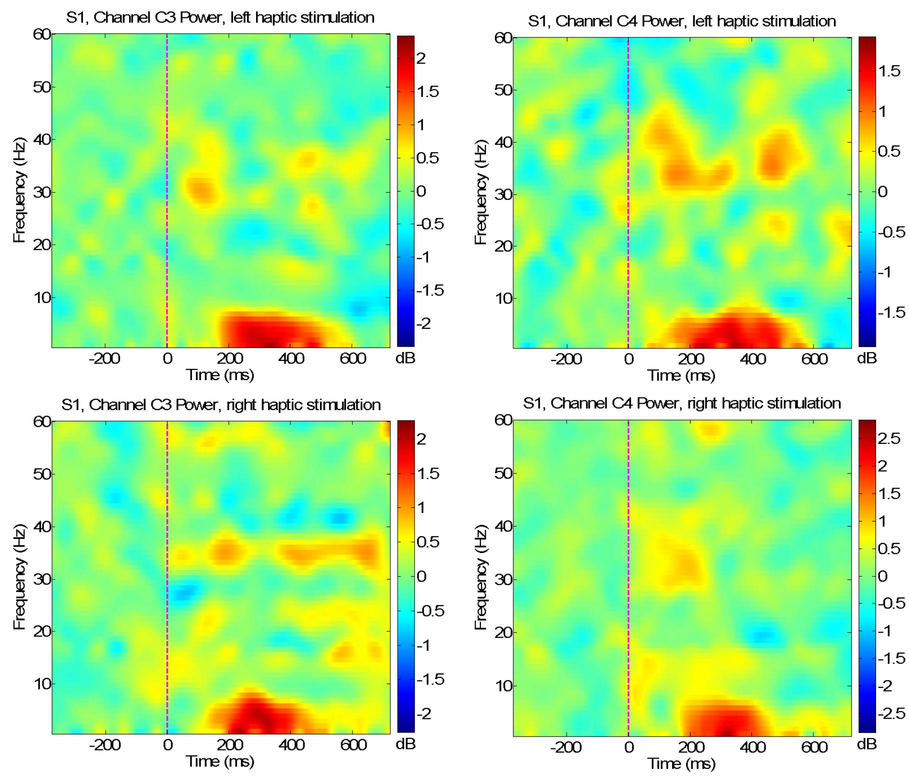

Figure 3.11: The average (N=309) TFR of the response to 200 ms long haptic stimulation at 200 Hz on both sides of the neck for S1, measured at C3 and C4. A response related to the haptic stimulation can be seen in 30-40 Hz range in each picture.

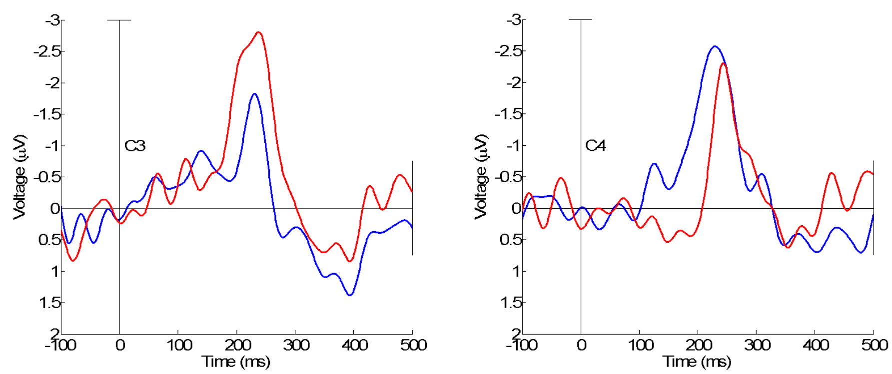

Figure 3.12: ERPs to haptic stimulation for S1 at C3 and C4, low-pass filtered below 8 Hz; the stimulation onset is at 0 ms and continues for 200 ms at 200 Hz. The blue line corresponds to stimulation at the left side of the neck and red line corresponds to stimulation at the right side of the neck.

Chapter 4

Discussion

These results show that subject learning with haptic feedback is equivalent to visual feedback for brain-computer interfaces. On average the accuracies were 67-68% for both haptic and visual feedback. The subjects also reported that haptic feedback was natural and more comfortable than visual feedback. In the short 41-min experiment with 9 sessions the subjects achieved high accuracies up to 88.8% with the BCI. These accuracies are in accordance with the respective posterior probabilities of the features produced by the Markov Chain Monte Carlo feature selection algorithm on the data with continuous kinesthetic imagery of the hand movements; each subject that had features with stable center frequency and electrode locations achieved average accuracies above 70%. The selected strategy enabled the improvement of selected features during the first few sessions while the subject was learning; however, the features selected for S1-S4 after the session 3 remained close to the best features calculated from sessions 4 to 9, indicating a high efficiency of the feature selection strategy. The selected features were stable and can be seen by eye in both the averaged and non-averaged TFRs. For S5 and S6 the features were unstable over the sessions and do not show in the TFRs. Haptic feedback with vibrotactile stimulation elements shows only minor interference in the used frequency band 8-30 Hz; the associated event related potentials, although existing, have no effect on the classification of frequency band features. The distractive environment displayed on the monitor during the feedback did not seem to prevent feature selection and high level of control for S1-S4; S5 and S6 might have been affected by the distractions.

The counterbalance of visual and haptic feedback allows the assessment of the efficiency during training, without biasing the results to either of the feedback modalities. The small number of subjects, however, renders the reliability of these results questionable; the within-subject accuracies in individual sessions become important. To avoid tiring the subjects, we designed the experiment to be as short as possible; in spite of this, some of the subjects reported tiring and loss of concentration towards the end of the experiment. The results also depended on the individual subject alertness and motivation over the sessions. The motivation was affected by frustration, which was a typical response to negative feedback; the subjects felt contradictory feedback to be disturbing. The subjects received feedback only once every second based on the linear model used as the classifier. The linear model has limited pattern recognition capacity and thus would potentially provide non-optimal performance. Regarding the detection of band power shifts, the linear model might provide more stable output. In turn, subjects could learn to control the BCI more easily than using the output of more complex classifiers. The online trained classifier provided up-to-date feedback for the subjects, but the risk of biasing the model towards one of the classes increased considerably, especially when subject demonstrated unstable features. Feedback received once every second might prove to be too seldom to properly facilitate learning; the learning is affected by the reaction times of the classifier, which are at best 1 s with filter lengths of 2 s. The discrete feedback presented for 200 ms with both haptic and visual modalities makes them comparable. However, possible advantages of continuous feedback should be investigated further.

The effectiveness of haptic feedback has mostly been investigated previously in other fields than brain-computer interfaces. A study on tactile icon (tacton) discrimination showed that vibrotactile stimulation can successfully communicate information by varying roughness and rhythm of the stimulation (Brown et al., 2005). These tactile icons would increase the information content of the feedback when applied to brain-computer interfaces. Investigations of haptic feedback in conjunction with visual and auditory feedback in a collaborative environment showed significant improvements in actual task performance of the subjects and performance perceived by the subjects (Sallnäs et al., 2000).

Recent findings indicate that for both experienced and inexperienced subjects receiving multimodal feedback the performance in a drag-and-drop task was improved; inexperienced subjects, however, performed poorly when haptic and visual feedback modalities were combined (Jacko et al., 2004). These two studies would directly indicate performance improvements when learning brain-computer interface use with multimodal feedback. This is in contrast to multimodal experiments with brain-computer interfaces. In these studies, the subjects used self-regulated slow cortical potentials to control the brain-computer interface with visual, auditory, and combined feedback; the results in both of these studies indicate impaired learning in the combined condition. The results further show a significant advantage to visual feedback compared to auditory feedback (Hinterberger et al., 2004; Pham et al., 2005). In the present study as well as in our previous study (Kauhanen et al., 2006), we found no clear advantage to either haptic or visual feedback. The combined condition was not considered.

The classification accuracies achieved in our experiment were 67-68interaction and communication; accuracies 65-90processing ([7] Kubler:Unlocking:2001). Typical brain-computer interfaces have information transfer rates below 25 bits/min ([5] Wolpaw:2002). In this study, however, the determination of the information transfer rate is difficult because of continuous imagery without single trials, long and varied task lengths, and the feedback, which was given once every second. The purpose of the present study was essentially to compare training of subjects with haptic and visual feedback, with final feature selection following three short sessions. The feature selection algorithm analyzed data where subject were instructed to imagine the movement of left and right hand, which is the most common strategy to date in two class brain-computer interface; more efficient imagery choices, such as navigation and auditory imagery, could be used to enhance classification accuracies if required ([99] Curran:ImageryComparison:2003). In the present study the classifier, a linear model, was updated online, enabling up-to-date feedback during the sessions, which is uncommon in the literature. A multivariate linear model with online feature selection by regression and weighting was more successful than a static classifier with initialized weights ([98] McFarland:Regression:2005). Online update was similarly used in a brain-computer interface with a continuously adaptive classifier based on quadratic discriminant analysis, which required cues ([19] Vidaurre:Adaptation:2006).

There are only a few classifiers for brain-computer interfaces, which capable of online adaptation without cues such as extended Kalman filtering of gaussian kernels with partial labeling of samples ([27] Lowne:Adaptive:2006) and variational Bayesian Kalman filtering of a radial basis function network ([92] sykacek:2004). Adaptation of the classifiers is essential and beneficial for the brain-computer interfaces in both accuracy and long term stability. Some questions, such as how to combine the strengths of different approaches and how to adapt throughout continuous use, still remain open ([116] Millan:Adaptation:2007).

Our results suggest that haptic feedback could complement or even substitute visual feedback during brain-computer interface training and use. Previous studies found improved performance in high accuracy tasks; those tasks include the control of robotic wheelchairs, artificial arms, and complex assistive devices. Haptic feedback would also make vision free for other observation tasks. Individuals with blindness would gain a substituting information channel, and would be able to communicate and observe more freely. With multiple vibrotactile elements and a variety of tactile icons the accuracy and information content of the channel would increase greatly. This development is essential for tetraplegic and ALS patients who potentially have residual sensing capabilities at the base of their neck; the neck area would provide a minimally disturbing way to convey the additional information from the applications to the patient. Further studies are required to confirm the usefulness of haptic feedback for tetraplegic patients. The current technology with EEG, given enough training, has been shown to be adequate to everyday interaction for the patients; invasive alternatives evaluated in monkeys (Santhanam et al., 2006) and human patients (Hochberg et al., 2006) might eventually prove to be more accurate and efficient, although currently most tetraplegic and ALS patients refuse surgical operations. The brain-computer interface systems have to be made more reliable, robust, cost-effective, and easy to use for non-expert caregivers in home environments. To achieve those goals, the systems need to be made fully adaptive without requiring constant calibration and intervention. Haptic feedback should help achieve these goals in future brain-computer interfaces.

Bibliography

ACNS (2006). Guidelines for standard electrode position nomenclature. American Clinical Neurophysiology Society. http://www.acns.org/pdfs/ACFDD46.pdf.

Birbaumer, N. (2006). Brain-computer-interface research: Coming of age. *Clinical Neurophysiology*, 117:479–83.

Birbaumer, N., Kubler, A., Ghanayim, N., Hinterberger, T., Perelmouter, J., Kaiser, J., Iversen, I., Kotchoubey, B., Neumann, N., and Flor, H. (2000). The thought translation device (ttd) for completely paralyzed patients. *IEEE Trans Rehabil Eng*, 8(2):190–3. 1063-6528 (Print) Journal Article.

Bishop, C. M. (1995). *Neural Networks for Pattern Recognition*. Oxford University Press.

Blankertz, B., Dornhege, G., Krauledat, M., Müller, K.-R., Kunzmann, V., Losch, F., and Curio, G. (2006). The berlin brain-computer interface: Eeg-based communication without subject training. *IEEE Transactions on neural system and rehabilitation engineering*, 14(2):147–52.

Brown, L. M., Brewster, S. A., and Purchase, H. C. (2005). A first investigation into the effectiveness of tactons. *Proceedings of the First Joint Eurohaptics Conference and Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems (WHC'05)*, pages 167–76.

Burde, W. and Blankertz, B. (2006). Is the locus of control of reinforcement a predictor of brain-computer interface performance. *Proceedings of the 3rd international brain-computer inferface workshop and training course 2006*, pages 76–7.

Cabeza, R. and Nyberg, L. (2000). Imaging cognition ii: An empirical review of 275 pet and fmri studies. *Cognitive Neuroscience*, 12(1):1–47.

Cincotti, F., Bianci, L., Birch, G., Guger, C., Mellinger, J., Scherer, R., Schmidt, R. N., Suárez, O. Y., and Schalk, G. (2006). Bci meeting 2005—workshop on technology:

Hardware and software. *IEEE Transactions on neural system and rehabilitation engineering*, 14(2):128–31.

Curran, E. and Stokes, M. (2003). Learning to control brain activity: A review of the production and control of eeg components for driving brain-computer interface (bci) systems. *Brain and Cognition*, 51:326–36.

David, O., Kiebel, S. J., Harrison, L. M., Mattout, J., Kilner, J. M., and Friston, K. J. (2006). Dynamic causal modeling of evoked responses in eeg and meg. *Neuroimage*, 30:1255–72.

Decety, J. (1996). The neurophysiological basis of motor imagery. *Behavioural Brain Reseach*, 77:45–52.

Egner, T. and Gruzelier, J. (2004). Eeg biofeedback of low beta band components: frequency-specific effects on variables of attention and event-related brain potentials. *Clinical Neurophysiology*, 115:131–9.

Farwell, L. and Donchin, E. (1988). Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. *Electroencephalography and clinical Neurophysiology*, 70:510–23.

Gazzaniga, M. S., Ivry, R. B., and Mangun, G. R. (2002). *Cognitive Neuroscience*. W. W. Norton & Company.

Glaser, R. and Bassok, M. (1989). Learning theory and the study of instruction. *Annual reviews of psychology*, 40:631–66.

Green, P. J. (1995). Reversible jump markov chain monte carlo computation and bayesian model determination. *Biometrika*, 82(4):711–32.

Guger, C., Edlinger, G., Harkam, W., Niedermayer, I., and Pfurtscheller, G. (2003). How many people are able to operate an eeg-based brain-computer interface (bci)? *IEEE Trans Neural Syst Rehabil Eng*, 11(2):145–7. 1534-4320 Clinical Trial Journal Article Validation Studies.

Hikosaka, O., Nakamura, K., Sakai, K., and Nakahara, H. (2002). Central mechanisms of motor skill learning. *Current opinion in neurobiology*, 12:217–22.

Hinterberger, T., Neumann, N., Pham, M., Kübler, A., Grether, A., Hofmayer, N., Wilhelm, B., Flor, H., and Birbaumer, N. (2004). A multimodal brain-based feedback and communication system. *Experimental Brain Research*, 154:521–26.

Hochberg, L. R., Serruya, M. D., Friehs, G. M., Mukand, J. A., Saleh, M., Caplan, A. H., Branner, A., Chen, D., Penn, R. D., and Donoghue, J. P. (2006). Neuronal ensemble control of prosthetic devices by a human with tetraplegia. *Nature Articles*, 442(13):164–71.

Hämäläinen, M., Hari, R., Ilmoniemi, R. J., Knuutila, J., and Lounasmaa, O. V. (1993). Magnetoencephalography—theory, instrumentation, and applications to noninvasive studies of the working human brain. *Reviews of Modern Physics*, 65(2):413–97.

Jacko, J., Emery, V. K., Edwards, P. J., Ashok, M., Barnard, L., Kongnakorn, T., Moloney, K. P., and Sainfort, F. (2004). The effects of multimodal feedback on older adults' task performance given varying levels of computer experience. *Behaviour & Information Technology*, 23(4):247–64.

Jeannerod, M. and Frak, V. (1999). Mental imaging of motor activity in humans. *Current Opinion in Neurobiology*, 9(6):735–39.

Jylänki, P., Menendez, R., Cincotti, F., Kauhanen, L., and Vehtari, A. (2006). A bayesian approach to select linearly separable spectral feature combinations. *Proceedings of the "Challenging Brain Computer Interfaces: Neural Engineering Meets Clinical Needs in Neurorehabilitation" - MAIA Workshop, November 9-10, Fondazione Santa Lucia, Rome, Italy*, page 18.

Kaminski, M., Ding, M., Truccolo, W., and Bressler, S. (2001). Evaluating causal relations in neural systems: granger causality, directed transfer function and statistical assessment of significance. *Biological cybernetics*, 85:145–57.

Kauhanen, L., Palomäki, T., Jylänki, P., Aloise, F., Nuttin, M., and Millan Jdel, R. (2006). Haptic feedback compared with visual feedback for bci. *Proceedings of the 3rd international brain-computer interface workshop and training course 2006*, pages 66–7.

Kubler, A., Kotchoubey, B., Kaiser, J., Wolpaw, J. R., and Birbaumer, N. (2001). Brain-computer communication: unlocking the locked in. *Psychol Bull*, 127(3):358–75. 0033-2909 (Print) Journal Article Review.

Kübler, A., Mushahwar, V., Hochberg, L., and Donoghue, J. (2006). Bci meeting 2005—workshop on clinical issues and applications. *IEEE Transactions on neural system and rehabilitation engineering*, 14(2):131–4.

Lemm, S., Blankertz, B., Curio, G., and Muller, K. R. (2005). Spatio-spectral filters for improving the classification of single trial eeg. *IEEE Trans Biomed Eng*, 52(9):1541–8. 0018-9294 (Print) Clinical Trial Journal Article.

Lotze, M. and Halsband, U. (2006). Motor imagery. *Journal of Physiology - Paris*, 99:386–95.

Mason, S., Kronegg, J., Huggins, J., Fatourechi, M., and Schlögl, A. (2006). Evaluation the performance of self-paced brain-computer interface technology, revision 1.0 (draft). http://www.bci-info.tugraz.at/Research_Info/documents/articles/self_paced_tech_report-2006-05-19.pdf.

Mason, S. G., Bohringer, R., Borisoff, J. F., and Birch, G. E. (2004). Real-time control of a video game with a direct brain-computer interface. *Journal of Clinical Neurophysiology*, 21(6):404–8.

McCullagh, P. and Nelder, J. A. (1989). *Generalized Linear Models*, volume 37 of *Monographs on Statistics and Applied Probability*. Chapman & Hall, second edition.

McFarland, D. J., Anderson, C. W., Müller, K.-R., Schlögl, A., and Krusienski, D. J. (2006). Bci meeting 2005—workshop on bci signal processing: Feature extraction and translation. *IEEE Transactions on neural system and rehabilitation engineering*, 14(2):135–8.

McFarland, D. J., McCane, L. M., and Wolpaw, J. R. (1998). Eeg-based communication and control: short-term role of feedback. *IEEE transactions on rehabilitation engineering*, 6(1):7–11.

Millan Jdel, R. and Mourino, J. (2003). Asynchronous bci and local neural classifiers: an overview of the adaptive brain interface project. *IEEE Trans Neural Syst Rehabil Eng*, 11(2):159–61. 1534-4320 (Print) Journal Article.

Millan Jdel, R., Renkens, F., Mourino, J., and Gerstner, W. (2004). Noninvasive brain-actuated control of a mobile robot by human eeg. *IEEE Trans Biomed Eng*, 51(6):1026–33. 0018-9294 (Print) Journal Article.

Müller-Gerking, J., Pfurtscheller, G., and Flyvbjerg, H. (1999). Designing optimal spatial filters for single-trial eeg classification in a movement task. *Clinical Neurophysiology*, 110:787–98.

Neal, R. M. (1996). *Bayesian Learning for Neural Networks*. Springer.

Neal, R. M. (2003). Slice sampling. *The Annals of Statistics*, 31(3):705–67.

Neuper, C., Scherer, R., Reiner, M., and Pfurscheller, G. (2005). Imagery of motor actions: Differential effects of kinesthetic and visual-motor mode of imagery in single-trial eeg. *Cognitive Brain Research*, 25:668–77.

Niedermeyer, E. and Lopes da Silva, F. H. (1999). *Electroencephalography: Basic Principles, Clinical Applications, and Related Fields*. Lippincott Williams & Wilkins, fourth edition.

Nuttin, M., Demeester, E., Vanhooydonck, D., and Van Brussel, H. (2001). Shared autonomy for wheel chair control: attempts to assess the user's autonomy. *Autonome Mobile Systeme*, 17:127–33.

Obermaier, B., Guger, C., Neuper, C., and Pfurtscheller, G. (2001). Hidden markov models for online classification of single trial eeg data. *Pattern Recognition Letters*, 22(12):1299–309.

Penny, W. D. and Roberts, S. J. (1999). Dynamic models for nonstationary signal segmentation. *Computers and biomedical research*, 32(6):483–502.

Pfurtscheller, G. (1992). Event-related synchronization (ers): an electrophysiological correlate of cortical areas at rest. *Electroencephalography and Clinical Neurophysiology*, 83(1):62–9.

Pfurtscheller, G., Guger, C., Muller, G., Krausz, G., and Neuper, C. (2000). Brain oscillations control hand orthosis in a tetraplegic. *Neurosci Lett*, 292(3):211–4. 0304-3940 Journal Article.

Pfurtscheller, G., Müller-Putz, G. R., Pfurtscheller, J., and Rupp, R. (2005). Eeg-based asynchronous bci controls functional electrical stimulation in a tetraplegic patient. *Applied Signal Processing*, 2005(19):3152–55.

Pfurtscheller, G. and Neuper, C. (2001). Motor imagery and direct brain-computer communication. *Proceedings of the IEEE*, 89(7):1123–33.

Pfurtscheller, G., Neuper, C., Muller, G. R., Obermaier, B., Krausz, G., Schlogl, A., Scherer, R., Graimann, B., Keinrath, C., Skliris, D., Wortz, M., Supp, G., and Schrank, C. (2003). Graz-bci: state of the art and clinical applications. *IEEE Trans Neural Syst Rehabil Eng*, 11(2):177–80. 1534-4320 (Print) Evaluation Studies Journal Article.

Pham, M., Hinterberger, T., Neumann, N., Kübler, A., Hofmayer, N., Grether, A., Wilhelm, B., Vatine, J., and Birbaumer, N. (2005). An auditory brain-computer interface based on the self-regulation of slow cortical potentials. *Neurorehabilitation and Neural Repair*, 19(3):206–18.

Rasmussen, C. E. and Williams, C. K. I. (2006). *Gaussian Processes for Machine Learning*. MIT Press.

Roberts, S. and Penny, W. (2000). Real-time brain-computer interfacing: a preliminary study using bayesian learning. *Medical & Biological Engineering and Computing*, 38:56–61.

Sallnäs, E.-L., Rassmus-Gröhn, K., and Sjöström, C. (2000). Supporting presence in collaborative environments by haptic force feedback. *ACM transactions on computer-human interaction*, 7(4):461–76.

Sanes, J. and Donoghue, J. (2002). Plasticity and primary motor cortex. *Annual Reviews of Neuroscience*, 23:393–415.

Santhanam, G., Ryu, S. I., Yu, B. M., Afshar, A., and Shenoy, K. V. (2006). A high-performance brain-computer interface. *Nature Letters*, 442(13):195–8.

Schalk, G., McFarland, D. J., Hinterberger, T., Birbaumer, N., and Wolpaw, J. R. (2004). Bci2000: a general-purpose brain-computer interface (bci) system. *IEEE Trans Biomed Eng*, 51(6):1034–43. 0018-9294 Evaluation Studies Journal Article.

Schreiber, T. (2000). Measuring information transfer. *Physical review letters*, 85(2):461–64.

Stinear, C. M., Byblow, W. D., Steyvers, M., Levin, O., and Swinnen, S. P. (2006). Kinesthetic, but not visual, motor imagery modulates corticomotor excitability. *Experimental Brain Research*, 168:157–64.

Sykacek, P., Roberts, S. J., and Stokes, M. (2004). Adaptive bci based on variational bayesian kalman filtering: an empirical evaluation. *IEEE Trans Biomed Eng*, 51(5):719–27. 0018-9294 (Print) Evaluation Studies Journal Article Validation Studies.

Townsend, G., Graimann, B., and Pfurtscheller, G. (2006). A comparison of common spatial patterns with complex band power features in a four-class bci experiment. *IEEE Transactions on Biomedical Engineering*, 53(4):642–51.

Vaughan, T. M. (2006). Home use of a brain-computer interface (bci): Initial studies. Personal communication at the 3rd International BCI Workshop and Training Course 2006, Graz, Austria.

Vidal, J. (1977). Real-time detection of brain events in eeg. *Proceedings of the IEEE*, 65(5):633–41.

Vidal, J. J. (1973). Toward direct brain-computer communication. *Annual Review of Biophysics and Bioengineering*, 2:157–80.

Villringer, A., Planck, J., Hock, C., Schleinkofer, L., and Dirnagl, U. (1993). Near infrared spectroscopy (nirs): a new tool to study hemodynamic changes during activation of brain function in human adults. *Neuroscience letters*, 14(154):101–4.

Wang, Y., Wang, R., Gao, X., Hong, B., and Gao, S. (2006). A practical VEP-based brain-computer interface. *IEEE Transactions on neural system and rehabilitation engineering*, 14(2):234–9.

Wexler, M., Kosslyn, S., and Berthoz, A. (1998). Motor processes in mental rotation. *Cognition*, 68:77–94.

Willingham, D. (1998). A neuropsychological theory of motor skill learning. *Psychological review*, 105(3):558–84.

Wills, S. A. and MacKay, D. J. (2006). DASHER—an efficient writing system for brain-computer interfaces? *IEEE Transactions on neural system and rehabilitation engineering*, 14(2):244–6.

Wolpaw, J. R., Birbaumer, N., McFarland, D. J., Pfurtscheller, G., and Vaughan, T. M. (2002). Brain-computer interfaces for communication and control. *Clin Neurophysiol*, 113(6):767–91. 1388-2457 Journal Article Review.

Wolpaw, J. R., Loeb, G. E., Allison, B. Z., Donchin, E., Nascimento, O. F., Heetderks, W. J., Nijboer, F., Shain, W. G., and Turner, J. N. (2006). Bci meeting 2005—workshop on signals and recording methods. *IEEE Transactions on neural system and rehabilitation engineering*, 14(2):138–41.

Wolpaw, J. R. and McFarland, D. J. (2004). Control of a two-dimensional movement signal by a noninvasive brain-computer interface in humans. *Proc Natl Acad Sci U S A*, 101(51):17849–54. 0027-8424 Journal Article.